

Supplementary online appendix to *Strategic Communication in Dictatorships: Performance, Patriotism, and Intimidation*

Abstract

This supplementary appendix consists of two sections. First, a *Descriptive Statistics* section provides additional details about the text corpus of legislative addresses of post-Soviet leaders. It also elaborates on the empirical text-as-data approach we use to identify leaders' communication strategies. Specifically, we present and explain the dictionary lists we relied on to estimate the latent semantic scaling scores and provide additional information and figures about the LSS method and our results. It also includes *Media Coverage of Presidential Address* and *Domestic Politics and Audiences in UNGA Speeches* subsections where we provide further details regarding the coverage and domestic audiences of legislative addresses and the UN speeches. In addition, we present summary statistics for the explanatory variables.

Next, the *Robustness Tests* section includes additional model specifications and robustness tests. First, we provide further details regarding the supplementary corpus of UN speeches, and include additional analyses. We also examine whether our results are sensitive to alternative sample selections both in terms of the countries included and the time covered. We then study whether various speech properties—including the type of speech, whether it was made in Russian or translated, text length, and other parameters—influence the results. In addition, we fit additional specifications with alternative measurements of the dependent variables, including sentiment analyses, dictionary analyses, and models estimated on the basis of the structural topic model. Lastly, we include specifications that test for alternative or supplementary explanations, or that include different explanatory variables. Overall, all these additional models support the main results reported in the paper.

Contents

1	Descriptive Statistics and Further Details Regarding Speeches	1
1.1	Text Data and Analyses	1
1.2	Media Coverage of Presidential Address	9
1.3	Domestic Politics and Audiences in UNGA Speeches	10
1.4	Description of Variables	13
2	Robustness Tests and Additional Analyses	14
2.1	Supplementary Analyses: UN General Debate Addresses	14
2.2	Robustness: Samples	16
2.3	Robustness: Dependent Variable	17
2.4	Additional Analyses	21

1 Descriptive Statistics and Further Details Regarding Speeches

1.1 Text Data and Analyses

At the center of our analyses is the text corpus of all legislative addresses made by presidents of post-Soviet states and leaders of six non-recognized entities. The full corpus consists of 304 annual texts from 1991 to 2019 from all 18 post-Soviet nation-states and unrecognized entities. Altogether, 51 individual political leaders are included in the corpus. Table 1 reports the summary statistics of text data per country. On average, speeches are quite long and typically delivered for over an hour; they include 345 sentences on average, 2,365 types, or unique forms of words, and 6,315 tokens, or words. The most verbose leaders in the text corpus are Smirnov of Transnistria, Shevardnadze of Georgia, Yeltsin of Russia, and Lukashenko of Belarus. Meanwhile, speeches made by presidents of Moldova as well as by leaders of the unrecognized states of LNR and Nagorno-Karabakh are the shortest. More specifically, the longest speeches based on the number of sentences and tokens are those by Lukashenko of Belarus in 2010, 2011, and 2012, Yeltsin of Russia in 1995 and 1999, and Nazarbayev of Kazakhstan in 2013. The shortest presidential speeches are by Bakiev of Kyrgyzstan in 2006 and Berdymukhamedov of Turkmenistan in 2012; the speeches by leaders of unrecognized entities, such as that of Pasechnik of LPR in 2017 and Saakyan of Artsakh in 2019, are also among the bottom five.

While we include all available speeches from the time of independence in 1991 over an almost thirty-year period to 2019, not all presidents made a presidential address to the parliament in their first year in office, or for that matter, every year. As we explain in the paper, in the early to mid-1990s, when politics was in flux and until the adoption of the first post-independence constitutions in the majority of post-Soviet countries, only a few presidents made speeches to parliaments. However, over time, the institution of the presidential address has gradually become the norm, and the majority of post-Soviet presidents are now required by the constitution to make an annual report.¹ The annual report is almost always a highly ceremonial, televised event delivered in person. On rare occasions, some presidents skip a personal appearance in the legislature and submit a written report instead, as President Yanukovich of Ukraine did in 2012 and 2013.

Table 2 provide further details regarding omissions in the text corpus. Altogether, we distinguish between three categories. Among them, 9 speeches were made, or almost certainly made that year, but we were unable to source them despite engaging local interlocutors. We also distinguish another category, that of when we have relevant speeches but are unable to use them. These are speeches by Shevardnadze of Georgia in 1999 and 2000, in Georgian, which are very poor scans of newspaper pages where his texts were published. We have attempted to process the texts using available optical text recognition (OCR), but we were unable to do so. Finally, we know that leaders exist who had the annual requirement to give an address that but did not comply with that requirement. There are 4 such leaders: Saakashvili of Georgia in 2008, Putin of Russia in 2017, Yushchenko of Ukraine in 2007, and Nazarbaev of Kazakhstan in 2013.

Despite formal constitutional requirements to make a report to parliament every year, on occasion presidents skip their duty in a given year. For instance, Putin skipped his annual duty in 2017; likewise, Yushchenko of Ukraine failed to make his report in 2007, which necessitated Ukrainian legislators to remind the president.² All addresses are delivered orally, even if presidents sometimes submit the written version of their address to the legislators before their speech.³ On only two occasions—and for only one specific leader—was the written version of the address published in official publications and/or governmental portals, and discussed by the cabinet and parliamentarians, but not made by the leader in person.⁴

¹For example, in Russia, the 1994 Constitution’s Article 84 states: “The President of the Russian Federation shall: f) address the Federal Assembly with annual messages on the situation in the country, on the guidelines of the internal and foreign policy of the State.”

²See the transcript, May 15, 2007, <http://portal.rada.gov.ua/meeting/stenogr/show/1426.html>.

³https://zn.ua/ukr/POLITICS/deputatam-vidali-fleshki-z-poyasnennyam-poslannya-poroshenka-do-radi-dokument-174811_.html, accessed June 7, 2018.

⁴Namely, President Yanukovich twice opted not to make a speech to parliament but instead sent his address to the

Country	Types	Tokens	Sentences	Texts	Years	Leaders
Armenia	1,904	4,679	227	9	2008–9, 2012–19	2
Azerbaijan	1,371	3,541	224	25	1994–6, 1998–2019	2
Belarus	4,073	12,258	837	23	1994, 1996, 1999–2019	2
Georgia	2,736	7,994	371	20	1994–8, 2001–2, 2005–7, 2009–19	4
Kazakhstan	2,647	6,546	385	28	1991–2019	2
Kyrgyzstan	1,811	4,090	237	21	1996, 1998–2004, 2006–2019	5
Moldova	690	1,326	56	17	200219	5
Russia	3,467	9,589	543	28	1991–2016, 2018–19	3
Tajikistan	2,725	8,393	287	15	2003, 200519	1
Turkmenistan	1,543	3,451	182	13	2001, 2003, 2005, 2009–19	2
Ukraine	2,088	4,811	267	26	1991–2019	6
Uzbekistan	2,448	6,372	257	17	1991–2, 2004–2019	2
Abkhazia	2,651	6,471	330	10	2001, 2006–19	4
DNR	1,556	3,645	229	6	2014–19	2
LNR	662	1,329	53	6	2014–19	2
Narorno-Karabakh (Artsakh)	794	1,531	73	4	2008, 2012, 2015, 2017–9	1
South Ossetia (SO)	1,909	4,523	242	7	2008, 2013–19	3
Transdnistria (PMR)	2,920	7,843	412	8	2010, 2012–19	3
Average	2,111	5,467	290	304	1991–2019	51

Table 1: *Post-Soviet Poslania Text Corpus* Note: The text corpus contains 304 statements delivered by national political leaders to parliaments (or closest speech to state-of-the-union address, if not available) from 1991–2019 (through 31 Dec 2019). Mean frequency reported for types, tokens and sentences in texts.

<i>Speeches not made/ requirement skipped</i>	<i>Speeches made but unavailable/ not able to locate</i>	<i>Speeches made, available, not used</i>
Saakashvili (Georgia) 2008 Putin (Russia) 2017 Yushchenko (Ukraine) 2007 Nazarbaev (Kazakhstan) 2013 ^a	Lukashenko (Belarus) 1997 Akayev (Kyrgyzstan) 1997 Niyazov (Turkmenistan) 2004 Ardzinba (Abkhazia) 2002-4 Khadzimba (Abkhazia) 2015 Kokoyty (North Ossetia) 2009-10	Shevardnadze (Georgia) 1999 and 2000
4	9	2

Table 2: *Omissions in Text Corpus* Note: We estimate that 11 texts, or 4 per cent (of 304 speeches in total) are omitted, either because we were unable to locate them (9) or unable to implement an OCR process (2). There are also 4 instances when presidents opted not make speeches in those years. ^aAs explained in text below, because there are two speeches in 2012 and no speech in 2013, in the analyses we use December 2012 speech for 2013 instead.

The timing of the presidential address may be relatively set, as when presidents deliver their annual speeches in the same month or even week of the month each year. The timing may also vary. In Belarus, until 2020 the annual address almost always took place in April or early May. In contrast, in Kazakhstan, it apparently may be delivered in any month of the year. In Russia, addresses always took place in the first half of the year until 2008, when the departing Vladimir

parliament of Ukraine in 2012 and 2013 in written form. As stated by his representative in parliament Yuri Miroshnichenko: “As you know, the president has the duty to send an annual message. The form in which this message is presented can be either in writing or in the form of a speech. [...] But, given that this document consists of a large number of pages, it is technically very difficult to announce,” Myroshnychenko said. He also said that the document consisted of 252 pages. When asked why the president did not present a 10-page message so that everyone would understand that the message was his and not simply one written by advisors, Miroshnichenko answered: “The President is not a person, but an institution.” See www.pravda.com.ua/news/2012/07/3/6967891/, accessed June 7, 2018, translated by the authors. For the 2012 and 2013 addresses in Ukraine, we therefore include only the opening remarks, which outline the contents of the written report, as these are written in a similar format to an oral speech, making them comparable to the other addresses in our dataset. Yanukovich, however, is the only leader who opted not to speak in person on two occasions, which further underlines the fact that annual legislative addresses are important opportunities for leaders to address the people and elite.

	<i>Performance</i> 1:	<i>Patriotism</i> 2:	<i>Intimidation</i> 3:
Legislative address	0.097** (0.045)	-0.084 (0.112)	-0.061 (0.080)
Translated text	0.005 (0.093)	-0.075 (0.061)	0.042 (0.081)
Text length	-0.007 (0.035)	-0.198** (0.062)	0.026 (0.044)
Unrecognized state	-0.041 (0.052)	-0.102 (0.104)	0.151+ (0.084)
Constant	-0.060 (0.280)	1.834** (0.481)	-0.130 (0.342)
Year dummy variables	yes	yes	yes
r^2	0.154	0.314	0.155
rmse	0.206	0.300	0.257
N countries	18	18	18
N	304	304	304

Table 3: *Accounting for Text Properties* Note: Models 1–3 are pooled linear models with country-robust standard errors; RMSE is root mean squared error, + $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Putin failed to make a report early in the year and the newly elected Medvedev delivered his address in November. Subsequent addresses were then scheduled very late in the year until President Putin, who returned to the presidency in 2012, chose not to address parliament in 2017 at all and instead did so in March 2018, thus returning the practice to the pre-2008 schedule.

On rare occasions, presidents may make two presidential addresses in the same year. In particular, Nazarbaev of Kazakhstan made addresses in January 2012 and then in December 2012; in January and November 2014; and in January and October of 2018. Because the first president of Kazakhstan did not make an address in 2013 and instead made policy plans for that year in his December 2012 address, we use that speech for 2013 instead. If, however, there is a speech in the following year, and the preceding year includes two speeches, we use only one of that year’s speeches in the panel analyses but retain the unused, second speech in the corpus.

We were able to locate almost all addresses in the 1991–2019 period,⁵ using various sources. First, we scraped legislative addresses from presidential or legislative web pages. Second, we sourced legislative addresses from the archives of national newspapers or official publications whenever speeches were not available from official web pages (e.g., [Kuchma, 2008](#)). Third, we often relied on national interlocutors to locate and scan the hard copies of relevant documents whenever such documents were not otherwise available.⁶

The annual speech is almost always referred to as an “address,” or “poslanie” in Russian. Not all speeches included in the corpus carry the title of a formal legislative address, however. In such cases, as we explain in the paper, we ascertain the most important speech that most closely resembles the annual legislative address. Altogether, 193 (65 percent) of speeches studied are addresses and the remainder are equivalent speeches, similar in content and format. In terms of content, for example, in Uzbekistan, the formal presidential address to the national parliament was given for the first time on December 22, 2017. This does not necessarily mean that there are no texts for the president of Uzbekistan for the preceding years. In fact, early each year, the

⁵We were unable to source around a dozen of speeches that were in fact made we could not source. For instance, Lukashenko of Belarus made legislative address in 1997 and 1998 but the national library did not include the hard copies of these addresses (In the analyses, we use an alternative policy speech on political and socio-economic development that Lukashenko made in 1998. Likewise, Georgia texts for 1999 and 2000 are omitted. We located the texts for 1999–2002 in the form of photocopies of relevant pages of the governmental newspapers. We were able to optically recognise texts for 2001 and 2002 but failed for 1999–2000 as these were of very poor quality and even a native speaker could not transcribe complete texts.

⁶Particular thanks for generous help to Svetlana Chetaikina on Kyrgyzstan, Lasha Gvelesiani and Tornike Zurabashvili on Georgia, Vasily Vashchanka on Kazakhstan and Aytan Gahramanova on Azerbaijan. The majority of texts were collected in 2016–17, since updated.

president has made an annual report to the cabinet of ministers nominally dedicated to the topic of socioeconomic development in the previous year. However, the contents of those reports to the cabinet, and of the 2017 address to the parliament, are not only about the economy but are substantially similar to the other speeches in our corpus. In Moldova, where legislative addresses are not available, the only regular annual speech is the one that the president of Moldova makes at a meeting with accredited diplomats: the speech is relatively short, but important issues and policy accomplishments are typically discussed. The president of Armenia also does not make formal legislative addresses. Here, we instead include programmatic speeches made before elections or at the ruling party conventions. Likewise, in Azerbaijan, where the president does not make a formal address, we rely on the annual Independence Day speeches, in which the president discusses both socioeconomic development and foreign policy. In the robustness section, we include the results based on a corpus in which we include alternative speeches made by the president of Azerbaijan.⁷

As we explain in the paper, almost all speeches, or 81 percent, were originally made in Russian, the post-Soviet *lingua franca*. For the remaining 11 percent, we used the official Russian translation, available from the presidential web pages, or used Google Translate. The Armenian, Georgian, Moldovan and Ukrainian presidents deliver legislative addresses in their native languages, but the official Russian translation is typically available (and Ukraine’s Yanukovich occasionally spoke in Russian). Whenever an official translation is not available, we had the text translated into Russian.⁸ Interestingly, some presidents who spoke in Russian occasionally included very short sections in their local languages, whether duplicating the same content or emphasizing different issues. In the latter case, such sections were also translated into Russian. Switching to a native language may be strategic in the sense that it serves a communicative purpose. Thus, in a speech made on November 11, 2014 by Nazarbayev of Kazakhstan, 19 percent of the text (543 out of 2,813 words in total) is in Kazakh. This is almost a twofold increase from the speech the year before, prior to the Russian annexation of Crimea and the conflict in Eastern Ukraine.

To make sure that variations in length, language, and whether a speech is a proper presidential address or an equivalent do not affect our results, we conducted a simple robustness test. Table 3 includes the results of our analyses that predict the same dependent variables as in the paper, using explanatory indicators to account for the properties of text, such as the type of speech, its length, and whether it was originally delivered in Russian. We also include an indicator for speeches made by leaders of unrecognized states to gauge whether they are different from those made by recognized states. Because the indicator for unrecognized states is time-variant, and that for whether the text is translated or made in Russian is largely time-invariant, the specifications included are pooled regression models. The results reported in Table 3 indicate that while leaders are somewhat more likely to discuss economic performance in formal legislative addresses, and leaders of unrecognized states are slightly more likely to use more intimidating language, the coefficients are only borderline statistically significant on these variables. The only significant coefficient is on the length of text—leaders who make longer speeches are less likely to use patriotic rhetoric. However, because the length of speech does not appear to matter for the other two communication strategies, overall we conclude that text properties have little impact on the substance of the speeches in our corpus.

Text analyses: Following translation, digitization, and optical text recognition whenever required, texts were transformed into a machine-readable format and pre-processed.⁹

We analyze the text corpus of authoritarian “state of the union” addresses by employing a semi-

⁷We also include speeches made by the leaders of unrecognized states. The leaders of Abkhazia, Transdnistria, and DNR make addresses in the same format as presidents, while for those from Nagorno-Karabakh, South Ossetia, and LNR we source the main programmatic speeches that cover domestic and foreign policy in a given year.

⁸Because we rely on the bag of words approach, following [de Vries, Schoonvelde and Schumacher \(2018\)](#) we used Google Translate for several speeches made in Ukrainian, Georgian, and Moldovan. For validation, we estimated the Wordscores for Ukrainian and Georgian speeches on two language corpora separately and found that the positions obtained were almost the same (0.93 coefficient).

⁹In the pre-processing of the texts, we first segmented speeches into sentences as the smallest but natural unit of analysis. The text corpus was pre-processed using the Quanteda package (version 3.0.0) in R ([Benoit and Nulty, 2013](#)). We removed function words, stop words, and tokens that contain numbers, symbols, and punctuation or those less than two characters long and stemmed the remaining words.

supervised machine learning method, Latent Semantic Scaling (LSS), which can classify documents based on specific pre-defined dimensions of theoretical interest (Watanabe, 2021). LSS has certain advantages over both supervised and unsupervised techniques. While the former demands significant resources as it requires training complex models on a large number of documents that have to be hand-coded, the latter is not well suited to analyzing pre-defined dimensions or categories such as the ones we are interested in. We can plausibly rely on unsupervised methods, such as the Structural Topic Model (STM) — which uses patterns of co-occurring words (“topics”) to discover latent themes (Roberts, Stewart and Tingley, 2016),— to evaluate the prevalence of “economic performance” speech, as economic terms can usually be clearly defined, even if STM entails a certain degree of post-hoc interpretation. However, it is not obvious whether “intimidating” and “patriotic” speech can be classified as separate substantive topics, as these types of rhetoric include the elements of what leaders speak about but also how they do so—the sentiment expressed in their political communication. Nonetheless, in the robustness section, we try to fit a STM model as an alternative method of measuring authoritarian communication strategies. Our results remain largely similar to those attained through the LSS approach.

<i>Intimidation</i>	<i>Performance/economy</i>	<i>Patriotism</i>
avantyrurist (adventurist)	ekonomik* (economy)	narod (people)
oppozits* (opposition)	ekonomichesk* (econom*)	nezavisimost* (independence)
anti-obshchestv* (anticommunit*/antisocietal)	razvit* (develop*)	obshchestv* (societ*)
ekstremis* (extremis)	rost (growth)	rodina (homeland, motherland)
terror* (terror*)	byudzet (budget)	patriot* (patriot*)
bor'b* (fight*)	kuput* (buy)	dukhovn* (spiritual, immaterial)
podstrekatel* (instigator*)	valyuta (currency)	sootchestvenn* (compatriot)
podryv (undermin*)	dolg (debt)	obshchenatsioan* (common national)
opponent (opponent)	deposit (deposit)	suverenitet (sovereignty)
provokats* (provocat*)	dollar (dollar)	depolitizats* (apolitical)
predatiel* (traitor*)		mnogoetnich* (multiethnic)
kuklovod* (puppeteer)		mezhnatsionaln* (interethnic)

Table 4: *Seed Words*. Note: Seed words for Intimidation, Performance, and Patriotism. See *dictionary.yml* file for complete list of words used in two languages and further details.

LSS also has certain advantages over dictionary-based analysis, including sentiment-based dictionaries. First, the latter requires the availability of relevant dictionaries that include terms related to performance-centered, patriotic, and intimidation language, in Russian. Despite the increased availability of various domain dictionaries (Grimmer and Stewart, 2013; Proksch et al., 2019; Young and Soroka, 2012), such specific Russian-language dictionaries, unfortunately, do not exist. Second, even if such dictionaries were available, other difficulties abound. The same term or phrase may be divisive in some contexts and cultures, and be completely innocent or even meaningless in others. Likewise, very specific historical references to the shared past that capture inclusive language in a given national context will be meaningless in other contexts. Again, as a robustness check (see below), we try to retest our main hypotheses using dictionary-based analyses, including sentiment analysis. Again, the findings remain largely the same as those attained through the LSS approach.

First, following Watanabe (2021), we carefully read a random sample of speeches and then selected as seed words a small set of words to define our three main variables of interest: economy-related performance, patriotism, and intimidating communication strategies. As shown in Table 4, to capture *Intimidating* language, we include such words as “adventurist,” “opposition,” “extremist,” “traitor,” “enemy,” and the like; *Patriotism* includes “people,” “independence,” “homeland” (motherland), “unity,” “patriotism,” etc., while *Performance/economy* includes “economy,” “development,” or “budget,” among other.

Next, polarity scores for all words are estimated on a unidimensional scale based on their semantic proximity to seed words, separately for the three types of speech. Specifically, we implement text analysis by relying on the LSS package (version 0.6.5) in R (Watanabe, 2021). In LSS, a vector-space model with 300 dimensions is constructed by singular-value decomposition of the

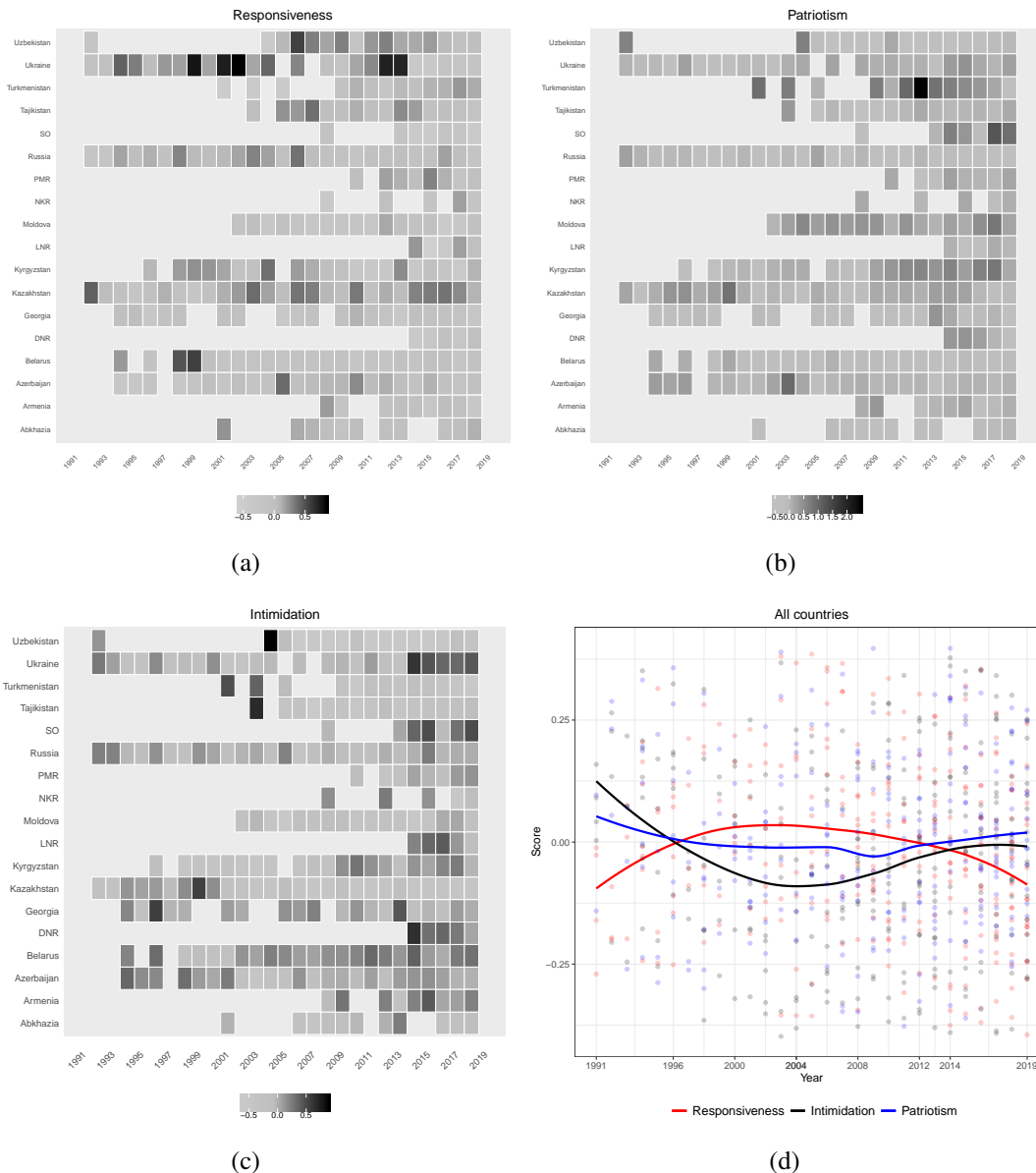


Figure 1: *LSS Scores for the Three Communication Strategies, Full post-Soviet Corpus*. Note: Subplot(d) plots average annual scores.

document-feature matrix, in which documents are unique sentences to capture similarity of words in immediate local contexts (Watanabe, 2021, 87). This technique, known as latent semantic analysis (LSA) (Deerwester et al., 1990), is considered one of the oldest word-embedding techniques. LSA excels in retrieving synonyms, while more recent word-embedding models focus on the identification of analogies, which are a more specific type of synonyms (Levy, Goldberg and Dagan, 2015).

Then, as we explain in the paper, we compute average scores for each speech, where more positive values stand for a higher propensity to engage in more intimidating, patriotism-based, or performance/economy-centered rhetoric. The resulting LSS scores range from about -0.5 to about +1. With the obtained scores, we can compare speeches on the three communicative dimensions of interest within and across ruler spells. To exemplify how scores vary, Subplot (d) in Figure 1 displays average annual scores for the three types of communication strategies for the whole corpus of speeches. One possible concern is whether rhetoric is significantly influenced by overall regional policy agenda changes in different periods (what are known as agenda shifts) (Manning, Raghavan and Schütze, 2008; Proksch and Slapin, 2009). The plot reveals that while post-Soviet leaders were somewhat more divisive in 1991–93, from the mid-90s the average regional scores

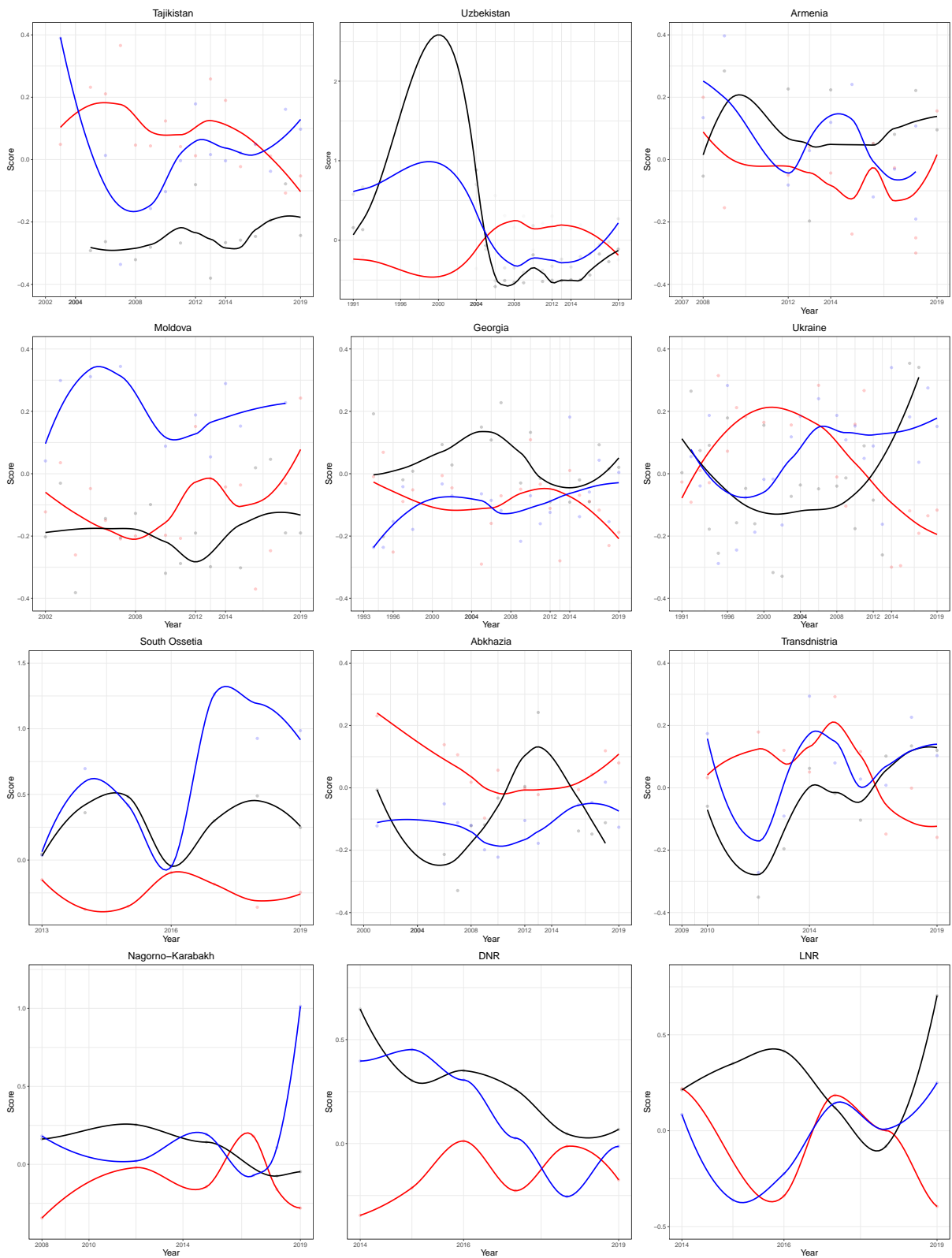


Figure 2: *Communication Strategies Over Time* Note: The figure shows those six countries, as well as the six non-recognized states not included in a similar figure in the main paper. Local polynomials for LSS scores on the three communication strategies on y-axes. Performance is red, patriotism is blue and intimidation is black.

remain relatively flat, indicating that the estimated differences are not determined by the structural conditions of transition.¹⁰ Additionally, Figure 1 displays average scores for the types of communicative strategies for the whole corpus of speeches. In turn, Figure 2 plots local polynomials for the three scores for speeches held in the six countries not included in a similar figure in the paper as well as the six unrecognized states.

Full Corpus of Vladimir Putin’s Speeches of Russia

Presidential addresses, whilst being important tools of regime legitimation, are delivered annually. They thus represent snapshots of authoritarian information management. To examine whether authoritarian rhetoric overall—not only rulers’ addresses, but all public speeches including during meetings with various officials, made to very different audiences, that vary in terms of their format and style—will on average be dictated by a similar logic as their most important annual addresses, we additionally examine the rhetoric of Vladimir Putin who is already included in the post-Soviet comparisons.

As a supplementary analysis of authoritarian communication, we estimate LSS scores for three communicative strategies, using the same procedure and same seed words as above, on a full corpus of Vladimir Putin of Russia’s speeches, sourced from (Braga, 2020). Altogether, the corpus includes 13,187 speeches, made between January 1, 2006 and December 31, 2016. We further categorise speeches depending on whether they are made by the president (6,443 texts), prime-minister (2,040), important cabinet members (1,913) and the ministry of foreign affairs (2,791). Next we identify 5,979 speeches made by Vladimir Putin specifically, as president (2006 to May 8, 2008, May 9, 2012 to 2016) and as prime-minister (May 10, 2008 to May 8, 2012).

Results are presented in Figure 3. As can be seen, from 2009 onwards, when Russia’s economy rapidly slows down, from 7 per cent on average in 2000–2008 to only 0.7 per cent from 2009–16, rhetoric centred on performance declines. Patriotism is prominent around 2008 and 2012 presidential elections, as well as from the beginning of the war against Ukraine. It also seems to increase as a result of the declining economy as the results in Tables 1 and 2 (in the paper) also indicate. We also observe a notable increase in a more intimidating rhetoric following the 2011–protests. In turn, the right sub-plot includes the results of communicative strategies based on a full corpus of 13,187 speeches. The results from the full corpus are similar to those estimated for Vladimir Putin separately, with the decline of patriotic rhetoric less steep for 2009–11 period however.

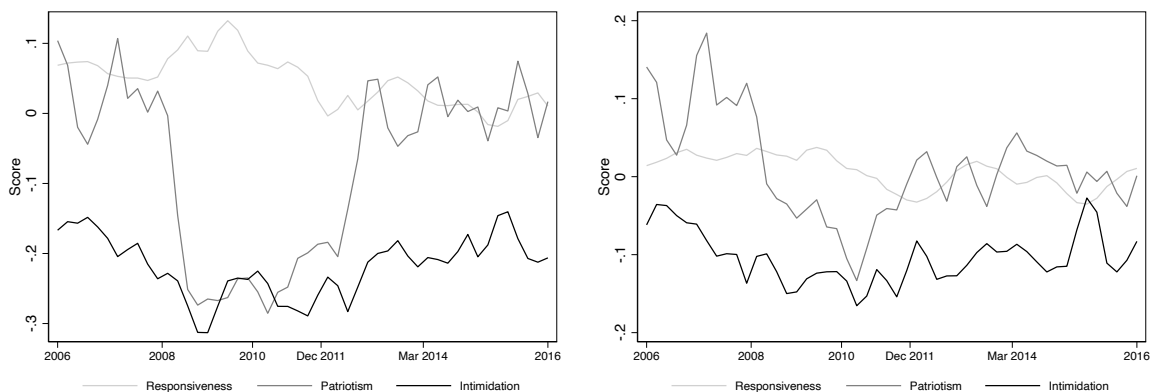


Figure 3: *Authoritarian Communication in Russia*. Note: Local polynomials of average scores per speech, based on all official texts by Vladimir Putin (left); based on all speeches from Russia’s presidential office, prime-minister’s office and the cabinet, and the ministry of foreign affairs (right).

¹⁰Also, across all model specifications, we include annual year dummies to account for possible time effects.

1.2 Media Coverage of Presidential Address

To assess the magnitude of coverage of the presidential address and the likely size of the domestic audience, we searched the *Factiva* news database, as explained in the main paper. We limit the search to Russia and Kazakhstan for illustrative purposes. Furthermore, these two countries have a better inclusion of national news outlets in comparison to other post-Soviet countries. In the paper, we show how much media attention presidential addresses receive in comparison to major national holidays. To arrive at this, on December 15-17, 2021 we thus searched for “presidential address” (“poslanie prezidenta”) and “victory day” (“den’ pobedy”) in all Russian-language media included in the *Factiva* database for the period from January 1, 2018 to December 15, 2021, on a monthly basis. For Kazakhstan, we did the same search and for the same period, and in addition, we searched for “Independence day” (“den’ nezavisimosti”), held on December 16 and regarded as the country’s main national holiday. Because the coverage improves over time, so that the database includes fewer news sources in the past, we decided to limit the analyses to the period beginning in January 2018.

As there are more Russian media outlets than those in Kazakhstan, and consequently because there are more Russian news sources included in *Factiva* than news sources from Kazakhstan, Russia’s address attracts many more references than the presidential address in Kazakhstan. For instance, Putin’s March 2018 speech attracted 909 references, and his January 2020 speech garnered 1548 references, as recorded in *Factiva*. In comparison, Nazarbaev’s January 2018 speech has 451 references and that of his successor, Kassim-Jomart Tokayev, in September of 2019 has 332 references. This, however, does not mean that the address received lower coverage or that it attracted less attention among its domestic audience. Rather, Kazakhstan has a smaller Russian-language media market than Russia and is less well covered in the *Factiva* database.

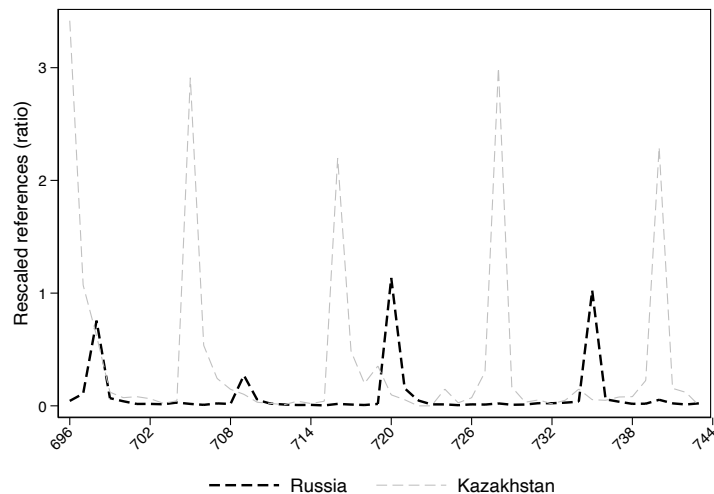


Figure 4: *Media Coverage of Presidential Address, Rescaled References*. Note: Total number of references to presidential address is rescaled to the total number of references to “sport” in national media in Russian and Kazakhstan, based on *Factiva* database. Four addresses in Russia and in Kazakhstan have increased coverage in respective months, as seen from the figure.

Therefore, we additionally decided to compare the coverage in Russia and Kazakhstan by rescaling the number of references to the presidential address to the monthly number of references to the word “sport” in both countries. We regard “sport” as a baseline term that is always encountered in the media. By rescaling the number of references to addresses to the total number of references to “sport” we are thus able to control for the mechanical increase in the number of stories. This also allows us to gauge the relative strength of coverage of the presidential address in Russia and Kazakhstan relative to the size of these countries’ overall media markets. Figure 4 plots the rescaled data for Russia and Kazakhstan. The results show that the coverage of presidential addresses shows the same patterns whether from the raw data, as included in the paper, or from the rescaled data, here. When we take into account the size of the national media markets, the coverage of presidential addresses in Kazakhstan is at least twice the size of that of Russia.

1.3 Domestic Politics and Audiences in UNGA Speeches

When leaders, foreign ministers, or other high-level national representatives address the United Nations General Assembly, they primarily address an international audience. However, because their speeches are also broadcast to domestic audiences, and covered in domestic print media, they simultaneously reach out to the domestic audience as well. If the UNGA addresses are indeed referenced, reproduced in full length, and/or discussed in national media, then we can expect to observe that their UNGA speeches would to a large extent follow the same strategic logic we find for domestic speeches.

To probe whether the UNGA addresses feature prominently in national media controlled by the authoritarian regime in question, and thus likely can be regarded as another important element in the propaganda, we used the following approach: First, because investigating how UNGA speeches are reproduced domestically in a national sample is both time and resource-demanding and is clearly worthy of a study in its own right, we have examined a sample of important autocracies over several years, as a plausibility probe. In the attempt to make the probe representative of the full population of authoritarian regimes, we tried to maximize geographical, state size, and regime-contextual variation given various data constraints, discussed below. For the period 2016–22, we thus analyzed the following countries: Russia and Kazakhstan (for which we also analyzed the domestic impact of the annual *poslanie*), as well as Zimbabwe, Qatar, Vietnam, and Iran. We thus have monarchies, personalist dictatorships, and one-party regimes from different regions of the world. Across the period, different national representatives make the address at the UNGA, and for some of the countries (Kazakhstan and Zimbabwe), we even have leadership changes. Due to language-skills constraints, we could only select countries with English and/or Russian-language news sources available.

Second, to make sure that we have access to the relevant national media outlets across these authoritarian countries, we analyze only the most recent period — a seven-year period from 2016 to 2022 (that is, UNGA Sessions 71-77).¹¹ For each country, we identified the national representative that made the address at the UNGA as well as the date the speech was made. Next, we identified one or more of the main regime-controlled newspapers accessible in either English or Russian and searched the outlet(s) around the relevant dates either through online archives or the Factiva news database.¹² As indicators of domestic attention to the UNGA speeches, we looked for three things: i) is the UNGA speech covered in the regime-controlled newspaper; ii) is the UNGA address reproduced in full length; and iii) is the UNGA address discussed also in different articles in the newspaper (e.g., by journalists, experts, or in editorials).

Table 5 below presents an overview of this plausibility probe. The table clearly shows that the UNGA speeches do reach domestic audiences in the analyzed countries. In all cases, throughout the period, speeches are always referred to in national media, and the content of the speeches is discussed or covered in other articles as well, in editorials as in Qatar and Zimbabwe in 2021,¹³ and are reported to be referenced by other national elites as in Iran in 2018.¹⁴ Moreover, in many cases, the national media also report how the speeches were praised by representatives of other countries (for example, see Vietnam in 2021¹⁵ and Qatar in 2022¹⁶). Most tellingly, in 29 out of

¹¹The relevant speaker was identified through the UNGA website <https://gadebate.un.org/en>.

¹²For the search, we relied on the following media outlets: Russia (*Rossiiskaya Gazeta*; *Argumenty i Fakty*; *ITAR-TASS*; *RIA Novosti*); Kazakhstan (*Kazinform*; *Kazakhstanskaya Pravda*); Qatar (*Gulf Times*; *The Peninsula*); Zimbabwe (*The Herald Zimbabwe*; *The Sunday Mail*); Vietnam (*Tuoi Tre News*; *Vietnam News Agency*; *Vietnam Plus*; *Nhan Dan*); Iran (*Tehran Times*).

¹³For Qatar, see <https://thepeninsulaqatar.com/editorial/22/09/2021/A-meaningful-address-to-UNGA>. For Zimbabwe, see <https://www.herald.co.zw/editorial-comment-more-energy-a-greener-world-are-possible/>.

¹⁴See <https://www.tehrantimes.com/news/427959/Cleric-warns-U-S-Israel-against-doing-anything-wrong>.

¹⁵See <https://en.vietnamplus.vn/czech-media-spotlights-vietnams-role-in-promoting-multilateral-cooperation-intl-law/208654.vnp> and <https://en.vietnamplus.vn/russian-newspaper-appreciates-vietnams-increasing-role-and-position/208717.vnp>

¹⁶See <https://www.gulf-times.com/story/724656/Chinese-ambassador-lauds-Amir-s-speech>.

the 42 country years analyzed, the speeches are quoted in full length. In the remaining 13 cases, large parts of the speeches appear as direct quotes in articles. Note also that these high numbers are based on a conservative test, as we only searched a few media outlets and only in English/Russian. It may thus very well be that speeches were brought in full length but that our restricted searches did not pick it up.

We have further read through a sample of 50 speeches made at the UN by authoritarian representatives. A few illustrative examples from UNGA speeches held by representatives from authoritarian countries clearly show that speakers do not only address an international audience but also speak directly to their domestic audience, and significant parts of their speeches follow the same strategic logic as outlined in the paper. For example, in 2006, when Azerbaijan was experiencing whopping GDP growth of more than 30%, Minister of Foreign Affairs, Elmar Mammadyarov indeed emphasized economic performance and talked a lot about domestic economic reforms, as also proposed in Hypothesis 2a:

“Let me now describe the economic outlook for Azerbaijan and its experience in enhancing growth, development, and social well-being. In light of trends in 2005, gross domestic product is expected to increase by 30.5 percent in 2006, driven by oil and gas production and exports. In 2006, State spending has been increased by up to 65 percent, a large proportion being spent on the public sector and infrastructure. The key challenge facing the Government is to create a favorable environment for investment in the non-oil sector and to diversify exports. To achieve this objective, it must keep domestic reforms on track and strive to strengthen the business environment.”

Similar, at the time of high domestic economic growth, in 2003, Chinese foreign minister, Li Zhaoxing, boasts his country’s economic performance in his speech:

China has kept its economic growth in high gear. The first two quarters saw the nation’s gross domestic product grow by 8.2 per cent over the corresponding period of last year, and foreign trade grow by 39 per cent. China’s economic efficiency has improved markedly, and its reforms on all fronts are progressing in an orderly way. Needless to say, China is a developing country. It still has a long way to go before all its citizens can live a comfortable, even affluent life. Development, therefore, remains China’s top priority.

Another example, this time on the use of patriotism in connection with elections (Hypothesis H1b) is found in President Mugabe of Zimbabwe 2007 speech to the UN — half a year before the contested 2008 March presidential elections, where the Mugabe regime was seriously challenged by the MDC opposition movement under the leadership of Morgan Tsvangirai:

“The British and the Americans have gone on a relentless campaign of destabilizing and vilifying my country. They have sponsored surrogate forces to challenge lawful authority in my country. They seek regime change. It is they who seek regime change, not my people. But they think they are entitled to change governments, placing themselves in the role of the Zimbabwean people in whose collective will democracy places the right to define and change regimes. [...] Mr. Bush and Mr. Brown have no role to play in our national affairs. They are outsiders - and mischievous outsiders - and should therefore keep out. The colonial sun set a long time ago in Africa - in 1980 in the case of Zimbabwe. And hence, Zimbabwe will never be a colony again — never, ever.”

Similar elements are visible in Syria’s foreign minister, Walid Al-Moualem, 2014 speech in the immediate aftermath of the June presidential elections:

“I would like to emphasize that the Syrian people have made their choice. Those who want to speak on behalf of the people must first be representatives of the people and, secondly, must respect the people’s will and their decisions. Any dialogue must therefore be based on respect for the will of the Syrian people and their decisions. Accordingly, we are open to a political solution in Syria with a genuine opposition that seeks the prosperity, stability and security of Syria — an opposition that does not depend on external elements and speak on their behalf, an opposition that has an impact in Syrian territory and has deep roots inside Syria, not in hotels and Western capitals.”

Likewise, the UNGA speech by Venezuela’s Vice-President Ms. Delcy Rodríguez Gómez in 2019, amid massive popular protests led by the Western-supported opposition leader Juan Guaidó is filled with the language of intimidation as also suggested in Hypothesis 3:

Country (Year)	Autocrat	UNGA speaker	Speech		
			covered	quoted in full length	discussed
Iran (2022)	Sayyid Ali Hosseini Khamenei	Seyed Ebrahim Raisi	+	-	+
Iran (2021)	Sayyid Ali Hosseini Khamenei	Seyed Ebrahim Raisi	+	+	+
Iran (2020)	Sayyid Ali Hosseini Khamenei	Hassan Rouhani	+	+	+
Iran (2019)	Sayyid Ali Hosseini Khamenei	Hassan Rouhani	+	+	+
Iran (2018)	Sayyid Ali Hosseini Khamenei	Hassan Rouhani	+	+	+
Iran (2017)	Sayyid Ali Hosseini Khamenei	Hassan Rouhani	+	+	+
Iran (2016)	Sayyid Ali Hosseini Khamenei	Hassan Rouhani	+	+	+
Kazakhstan (2022)	Kassym-Jomart Tokayev	Kassym-Jomart Tokayev	+	+	+
Kazakhstan (2021)	Kassym-Jomart Tokayev	Kassym-Jomart Tokayev	+	+	+
Kazakhstan (2020)	Kassym-Jomart Tokayev	Kassym-Jomart Tokayev	+	+	+
Kazakhstan (2019)	Kassym-Jomart Tokayev	Kassym-Jomart Tokayev	+	+	+
Kazakhstan (2018)	Nursultan Nazarbayev	Kairat Abdrakhmanov	+	-	+
Kazakhstan (2017)	Nursultan Nazarbayev	Kairat Abdrakhmanov	+	-	+
Kazakhstan (2016)	Nursultan Nazarbayev	Erlan Idrissov	+	-	+
Qatar (2022)	Tamim bin Hamad Al Thani	Tamim bin Hamad Al Thani	+	+	+
Qatar (2021)	Tamim bin Hamad Al Thani	Tamim bin Hamad Al Thani	+	+	+
Qatar (2020)	Tamim bin Hamad Al Thani	Tamim bin Hamad Al Thani	+	+	+
Qatar (2019)	Tamim bin Hamad Al Thani	Tamim bin Hamad Al Thani	+	-	+
Qatar (2018)	Tamim bin Hamad Al Thani	Tamim bin Hamad Al Thani	+	+	+
Qatar (2017)	Tamim bin Hamad Al Thani	Tamim bin Hamad Al Thani	+	+	+
Qatar (2016)	Tamim bin Hamad Al Thani	Tamim bin Hamad Al Thani	+	-	+
Russia (2022)	Vladimir Putin	Sergey Lavrov	+	+	+
Russia (2021)	Vladimir Putin	Sergey Lavrov	+	+	+
Russia (2020)	Vladimir Putin	Vladimir Putin	+	+	+
Russia (2019)	Vladimir Putin	Sergey Lavrov	+	+	+
Russia (2018)	Vladimir Putin	Sergey Lavrov	+	+	+
Russia (2017)	Vladimir Putin	Sergey Lavrov	+	+	+
Russia (2016)	Vladimir Putin	Sergey Lavrov	+	+	+
Vietnam (2022)	Nguyen Phú Trọng	Pham Binh Minh	+	+	+
Vietnam (2021)	Nguyen Phú Trọng	Nguyen Xuan Phuc	+	+	+
Vietnam (2020)	Nguyen Phú Trọng	Nguyen Phu Trong	+	+	+
		Nguyen Xuan Phuc ^a	+	+	+
Vietnam (2019)	Nguyen Phú Trọng	Pham Binh Minh	+	+	+
Vietnam (2018)	Nguyen Phú Trọng	Nguyen Xuan Phuc	+	-	+
Vietnam (2017)	Nguyen Phú Trọng	Pham Binh Minh	+	-	+
Vietnam (2016)	Nguyen Phú Trọng	Pham Binh Minh	+	-	+
Zimbabwe (2022)	Emmerson Mnangagwa	Emmerson Mnangagwa	+	+	+
Zimbabwe (2021)	Emmerson Mnangagwa	Emmerson Mnangagwa	+	-	+
Zimbabwe (2020)	Emmerson Mnangagwa	Emmerson Mnangagwa	+	+	+
Zimbabwe (2019)	Emmerson Mnangagwa	Emmerson Mnangagwa	+	+	+
Zimbabwe (2018)	Emmerson Mnangagwa	Emmerson Mnangagwa	+	+	+
Zimbabwe (2017)	Robert Mugabe	Robert Mugabe	+	-	+
Zimbabwe (2016)	Robert Mugabe	Robert Mugabe	+	-	+

Table 5: *UNGA speeches referenced in national media* Note: ^a In 2020–21, Vietnam was a non-permanent member of the Security Council and therefore both General Secretary Nguyen Phu Trong and President Nguyen Xuan Phuc were allowed to address the assembly.

The present massive anti-Venezuelan operation dates back to 2002, when the United States led a coup d'état against President Hugo Chavez, with the support of the very same actors today, unfortunately, attempting to overthrow our legitimate Government. Something occurred in Venezuela on 23 January that is without precedent in the world: a member of Congress elected with fewer than 90,000 votes stood in a public square and proclaimed himself president of Venezuela. That member of Congress is an imperial puppet. He has no political legitimacy in Venezuela; he is nothing more than an illegitimate and criminal tool, created to undermine stability and peace in the Bolivarian Republic of Venezuela. [...] We are facing the use of criminal gangs and drug-trafficking paramilitary groups to destabilize Venezuela. [...] The legitimate constitutional Government with effective territorial control and the institutional mechanisms of the rule of law continues, and will continue to be, that of President Nicolas Maduro.”

Similarly, earlier in 2007, prior to a constitutional referendum that was sought to scrap presidential term limits in Venezuela for Hugo Chavez, Nicolas Maduro, Vice-President at the time, resorts to intimidation language:

The world knows that there has been an ongoing conspiracy against the Venezuelan democracy and President Hugo Chavez. The world knows that in 2002 our people defeated an attempted coup d'etat that sought the destruction of democracy and the assassination of President Chavez. Today, the people of Venezuela are in the midst of a thorough reform of the Constitution. In December, the people of Venezuela, following a debate on terms and proposals related to constitutional reform, will go to the polls to decide in a sovereign manner what our country's future should be and what reforms we should undertake to expand the foundations of political, social and economic democracy. Today, we reaffirm to the world that we want respect for Venezuela's sovereignty and independence and an end to imperialist-led media campaigns that try to distort the real conditions of democracy building by our people and by our popular revolution.

The above example clearly shows not only that the speakers representing authoritarian governments employ similar communicative strategies in their domestic and international addresses alike but also that significant parts of the United Nations speeches are concerned directly with domestic political developments, such as forthcoming referenda.

1.4 Description of Variables

Table 6 reports the average, standard deviation, minimum and maximum values, and the total number of observations for the dependent variable and the explanatory variables employed throughout the paper and in the supplementary analyses. The full sample consists of 304 country-year observations; because the majority of indicators are not available for unrecognized states, the estimation sample is reduced by about a quarter. The explanatory variables for the post-Soviet corpus of speeches are presented in the paper.

For the analyses of communication strategies on the international stage, we rely on *Presidential election* and *Referendum*, $v2eltype_6$ and $v2ddyror$, from Coppedge et al. (2019). Because *Protests* from Clark and Regan (2016) are available from 1990 only, we gauge the existence of *Protests* based on whether there is a mass campaign against the government (Chenoweth and Shay, 2020). In turn, *Sanctions*, *Interstate dispute*, *GDP growth*, *GDP income per capita*, logarithm, *Colour revolutions* and *Closed autocracy* are the same variables as in the post-Soviet corpus.

Additionally, in the robustness section in this appendix, we include supplementary analyses that rely on several additional variables. Leaders' personal background variables, such as *Silovik*, *Ex-party sec.* and *Engineering degree* are from *Cursus Honorum* data set (Baturu, 2016), supplemented by the authors for missing leaders. In addition we also categorize *Military conflict*¹⁷ and *Energy dispute* — taking the value of 1 for Belarus in 2004 and 2006, Ukraine in 2006, 2008, 2009, and 2013–14, and Georgia in 2006 — for the robustness analyses that include unrecognized states. *Dictatorship* takes the value of 1 if the regime is categorized as unfree (Freedom House, 2011).

¹⁷Taking the value of 1 for Abkhazia in 2001, 2006, and 2008, Armenia in 2008, 2014 and 2016, Azerbaijan in 1994, 2010, 2014 and 2016, DNR and LNR in 2014–19, Georgia in 1998, 2001, 2006, and 2008, NKR in 2008, 2012, 2015, and 2017–19, Russia in 1994–96, 1999–2000, 2008, and 2014, and Ukraine in 2014–19.

Variable	Mean	Std. Dev.	Min.	Max.	N
Performance/Economy (LSS)	0.008	0.212	-0.555	0.835	304
Patriotism/Inclusive (LSS)	0.097	0.343	-0.509	2.478	304
Intimidation/Divisive (LSS)	-0.024	0.265	-0.616	0.884	304
Election year	0.207	0.406	0	1	304
Referendum	0.092	0.29	0	1	304
Economic growth	3.255	6.87	-22.551	32.997	256
GDP pc, log	7.995	0.811	6.19	9.380	257
Protests	3.824	7.553	0	91	245
Sanctions	0.068	0.101	0	0.287	220
Interstate disputes	0.794	1.287	0	6	257
Closed autocracy	0.139	0.346	0	1	245
First term	0.477	0.5	0	1	304
Color revolution	0.095	0.294	0	1	304
Silovik	0.218	0.413	0	1	303
Ex-party sec.	0.251	0.434	0	1	303
Engineering degree	0.3	0.459	0	1	303
Legislative address	0.72	0.45	0	1	304
Translated text	0.194	0.396	0	1	304
Text length	4385.48	3280.767	257	18002	304
Central Asia	0.329	0.471	0	1	304
Caucasus	0.273	0.446	0	1	304
Unrecognized state	0.155	0.362	0	1	304
Military conflict	0.141	0.349	0	1	304
Energy dispute	0.026	0.16	0	1	304
Closed dictatorship	0.533	0.5	0	1	304
UN data					
Performance/Economy (LSS)	-0.026	0.913	-2.347	5.789	2093
Patriotism/Inclusive (LSS)	-0.117	0.992	-2.983	4.82	2093
Negative sentiment	-0.898	0.432	-2.745	0.553	2093
Election year	0.119	0.324	0	1	1975
Referendum	0.017	0.13	0	1	2085
GDP growth	4.529	9.173	-64.047	149.973	1931
Protests	0.341	0.474	0	1	2093
Sanctions	0.145	0.314	0	1.005	2016
Interstate dispute	0.374	0.484	0	1	2093
GDP pc, log	3.712	0.529	2.461	5.082	1909
Autocracy	0.357	0.479	0	1	2093

Table 6: *Descriptive Statistics*

2 Robustness Tests and Additional Analyses

In this section we consider a range of alternative and supplementary explanations for the observed variation in the communication strategies of leaders.

2.1 Supplementary Analyses: UN General Debate Addresses

The texts of the UN General Debate are sourced from [Baturu, Dasandi and Mikhaylov \(2017\)](#). All texts are in English. The text corpus was again pre-processed using the Quanteda package (version 1.5.1) in R ([Benoit and Nulty, 2013](#)). Pre-processing included the removal of stop words, symbols, numbers, non-Latin characters, URL and hyphens, and punctuation; converting words to lower-case letters; and stemming ([Lucas et al., 2015](#)). We also used bigrams (word collocations). The corpus was further reduced by removing country-specific and rare words, i.e., all words that appear fewer than 50 times in the text corpus, and in fewer than 25 documents. We implement Latent Semantic Scaling (LSS) in the same manner as described in the section above ([Watanabe, 2021](#)). As seed words for *Performance*, we include the following terms: “economy,” “economic,”

	<i>Leaders</i>			<i>Nonleaders</i>		
	types	tokens	sentences	types	tokens	sentences
All Texts	849	2,554	97	1,004	3,231	119
Post Cold war	797	2,321	88.2	848	2,517	88.9
Democracy	838	2,488	96.3	962	2,984	116
Nondemocracy	871	2,683	99.7	1,034	3,404	121

Table 7: *UN Text Corpus* Note: *Types*: average frequency of unique forms of words (per text); *Tokens*: average frequency of words (per text). *Sentences*: average number of sentences (per text).

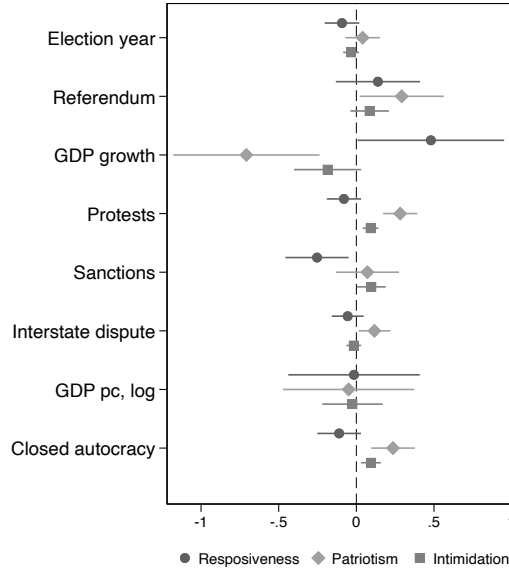


Figure 5: *Average Marginal Effects of Predictors on UN sample*. Marginal effects, following Model 2, 4 and 6, Table 2 (in the paper). Annual dummy variables are estimated but omitted from the graph.

“development,” “growth,” “budget,” “dollar,” “market,” “industry.” As seed words for *Patriotism*, we include “independence,” “patriot,” “patriotism,” “unity,” “people,” “multiethnic,” “traditional,” “sovereignty,” “citizen,” “tradition,” “motherland” or “ancestral”.

Because speakers at the UN tend to use more diplomatic language, as well as because specific terms that the post-Soviet authoritarian leaders rely on to intimidate and insult their political opponents are somewhat region-specific (e.g., anti-president*, oppozits*, podstrekatel*), we decided not to construct another, more general, dictionary of intimidating rhetoric and instead rely on sentiment analysis as a more general measure of negative and intimidating rhetoric. In the robustness section below, we also fit the same sentiment analysis on post-Soviet speeches and show that the results obtained from the sentiment analyses and those obtained from the LSS intimidation dictionary are similar. Specifically, we use the Lexicoder Sentiment Dictionary (Young and Soroka, 2012). We estimate the negative sentiment as a logarithm $\frac{negative+0.5}{positive+0.5}$. The descriptive statistics of the variables included in the analyses based on UN speeches are presented at the bottom of Table 6.

Marginal Effects: In the paper, in the interest of space, we did not include average marginal effects estimations following specifications fitted on the UN speeches. Figure 5 — which reports the predicted LSS scores following estimations from Models 2, 4 and 6, Table 2 (in the paper)— indicates that in terms of substantive effects, economic performance is the most important predictor of authoritarian speech strategies, followed by protests, sanctions, and referenda. The results are thus very similar to those obtained based on speeches to the domestic audiences.

Including Cold war UN speeches: Table 8 replicates the results of the communication strategies used at the UN level based on a sample that includes speeches made during the Cold War. Because the indicator for color revolutions is applicable for the post-Cold War period only, we exclude it here. Models 1, 3, and 5 are estimated on a sample of all autocracies in the world from 1971–2019, and Models 2, 4, and 6 on a sample of all closed autocracies from 1971–2019; that

	<i>Responsiveness</i>		<i>Patriotism</i>		<i>Intimidation</i>	
	<i>1:</i>	<i>2:</i>	<i>3:</i>	<i>4:</i>	<i>5:</i>	<i>6:</i>
Election year	-0.058 (0.043)	-0.081 (0.100)	0.023 (0.047)	-0.058 (0.114)	-0.025 (0.019)	-0.048 (0.046)
Referendum	0.073 (0.098)	0.258+ (0.146)	0.112 (0.106)	0.292+ (0.168)	0.033 (0.044)	0.168** (0.068)
Economic growth	0.003+ (0.002)	0.001 (0.002)	-0.005** (0.002)	-0.004 (0.003)	-0.001 (0.001)	0.001 (0.001)
Protests	-0.120** (0.039)	-0.196*** (0.056)	0.189*** (0.042)	0.172** (0.065)	0.092*** (0.018)	0.086** (0.026)
Sanctions	-0.280*** (0.082)	-0.329** (0.127)	0.265** (0.088)	0.390** (0.146)	0.080** (0.037)	0.057 (0.059)
Interstate dispute	-0.053 (0.035)	-0.004 (0.044)	0.138*** (0.038)	0.167*** (0.050)	0.022 (0.016)	0.049** (0.020)
GDP pc, log	0.099 (0.110)	0.290** (0.148)	0.352** (0.119)	-0.144 (0.170)	-0.048 (0.049)	-0.397*** (0.069)
Closed autocracy	0.024 (0.042)		0.140** (0.045)		0.025 (0.019)	
Constant	-1.187** (0.410)	-1.920*** (0.555)	-1.251** (0.442)	0.688 (0.638)	-0.611*** (0.183)	0.673** (0.258)
Year dummy variables	yes	yes	yes	yes	yes	yes
rmse	0.702	0.588	0.757	0.676	0.314	0.273
σ_u	0.506	0.461	0.615	0.571	0.210	0.276
ρ	0.342	0.381	0.398	0.416	0.310	0.505
N	3047	1392	3047	1392	3047	1392
N countries	118	86	118	86	118	86

Table 8: *Communicative Strategies at the International Stage — Alternative UN Sample Selection*
Note: Models 1, 3 and 5 are estimated on a sample of all autocracies from 1971–2019; Models 2, 4 and 6 — on a sample of all closed (only) autocracies from 1971–2019. Models 1–6 are panel linear models with country fixed effects; RMSE is root mean squared error, + $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

is, excluding electoral autocracies. The results indicate that the authoritarian speakers are sensitive to various threats, including sanctions and protests, as they are more likely to turn to intimidating rhetoric under these circumstances (Columns 5–6), and, by contrast, to emphasize economic performance when they face no such threats (Columns 1–2). They are also more likely to accentuate patriotism when there is an interstate dispute (Columns 3–4). However, the coefficients on *Election* and *Referendum* are not statistically significant, which suggests that these factors matter only in the post-Cold War period when the majority of dictatorships feature elections, even if not competitive.

2.2 Robustness: Samples

In the following, we present several analyses that examine whether our results are sensitive to sample selection.

Including unrecognized states: Because the predominant majority of explanatory variables are only available for states recognized by the international community, the observations for unrecognized states are excluded through listwise deletion; in the paper we relied on the analyses fitted on the sample of twelve post-Soviet countries, thus excluding the non-recognized states. Table 9 includes specifications fitted on a full sample that includes the six unrecognized states together with the twelve post-Soviet countries, based on several variables collected by the authors, as explained in the Descriptive Statistics section. Because we include time-invariant predictors, we fit pooled regressions instead of fixed effects specifications. As we do not have economic indicators for unrecognized states, understandably we have a poor prediction for the rhetoric centered on performance, as seen in the first column in Table 9. Like the results in the paper, intimidating rhetoric is stronger in a referendum year, while leaders tend to use more patriotic language in election years.

Excluding Ukraine, Georgia and Moldova: In turn, Table 10 (1–6) excludes the three hybrid

	<i>Performance</i> 1:	<i>Patriotism</i> 2:	<i>Intimidation</i> 3:
Election year	-0.021 (0.019)	0.107** (0.037)	0.007 (0.029)
Referendum	-0.092** (0.040)	0.111 (0.075)	0.161** (0.046)
Military conflict	-0.054 (0.068)	0.002 (0.073)	0.133 (0.077)
Energy dispute	0.010 (0.036)	0.029 (0.074)	0.050 (0.045)
Closed dictatorship	-0.035 (0.050)	-0.048 (0.080)	0.028 (0.055)
Color revolution	0.027 (0.032)	-0.109+ (0.055)	-0.025 (0.032)
Caucasus	-0.068 (0.054)	0.014 (0.087)	0.042 (0.053)
Unrecognized state	-0.039 (0.050)	0.082 (0.120)	0.022 (0.053)
Central Asia	0.040 (0.058)	0.164 (0.109)	-0.180** (0.068)
Constant	0.056 (0.069)	0.028 (0.088)	-0.029 (0.055)
r^2	0.082	0.075	0.218
rmse	0.206	0.335	0.238
N	304	304	304

Table 9: *Specifications with Unrecognized States Included* Note: Models 1–3 are pooled linear models with country-robust standard errors; RMSE is root mean squared error, + $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

regimes of Ukraine, Georgia, and Moldova; that is, the estimation sample includes only more authoritarian regimes. As can be seen, the results are very similar to those estimated on a larger sample, as leaders tend to discuss performance when the economy is good, turn to patriotism in election years, and to intimidation in referendum years. They are also influenced by sanctions and protests. However, with fewer observations, the results are understandably affected in these models, which also include more controls.

Alternative speeches for Azerbaijan: As discussed above, the president of Azerbaijan does not make annual reports to the people or the parliament as such. Instead, we used annual Independence Day speeches, in which the president discusses both socioeconomic development and foreign policy. However, there are also annual meetings on the regional Socio-Economic Development Programme when the president delivers more detailed socioeconomic reports but largely omits foreign policy. For robustness, we alter the text corpus and include the Azeri presidents’ socioeconomic reports instead of the Independence Day speeches we use in the paper. That is, all text analyses are re-estimated on this corpus in a separate estimation. Table 10 (7–12) includes the results of these specifications. The estimation sample is reduced by ten observations, but the results are almost identical to those in the paper.

2.3 Robustness: Dependent Variable

To identify the distinct communication strategies of authoritarian leaders, we rely on a semi-supervised machine learning method, Latent Semantic Scaling (LSS), as discussed in the paper. While we believe this method has significant advantages for our research design, other techniques to extract information from texts are possible. For instance, because we decided not to estimate intimidating rhetoric in the UNGA, as discussed above, we instead relied on the measure of negative sentiment. For robustness, therefore, we can also examine whether different methods to construct the dependent variables lead to results different from those obtained in the paper.

	Excluding Ukraine, Georgia and Moldova						with Alternative Speeches for Azerbaijan					
	Performance		Patriotism		Intimidation		Performance		Patriotism		Intimidation	
	1:	2:	3:	4:	5:	6:	7:	8:	9:	10:	11:	12:
Election year	-0.025 (0.038)	-0.030 (0.036)	0.190** (0.058)	0.198*** (0.058)	-0.022 (0.050)	-0.016 (0.050)	-0.039 (0.037)	-0.047 (0.037)	0.135** (0.053)	0.148** (0.053)	-0.008 (0.039)	0.006 (0.038)
Referendum	-0.142** (0.058)	-0.144** (0.055)	0.131 (0.087)	0.148+ (0.088)	0.234** (0.075)	0.248** (0.076)	-0.070 (0.056)	-0.073 (0.056)	0.105 (0.080)	0.118 (0.080)	0.145** (0.060)	0.150** (0.058)
Economic growth	0.008** (0.004)	0.009** (0.004)	-0.000 (0.005)	-0.002 (0.006)	-0.005 (0.005)	-0.007 (0.005)	0.011** (0.004)	0.011** (0.004)	-0.010 (0.006)	-0.010+ (0.006)	-0.007+ (0.004)	-0.007+ (0.004)
Protests	-0.008** (0.003)	-0.004 (0.003)	0.012** (0.005)	0.009+ (0.005)	0.008** (0.004)	0.006 (0.004)	-0.005** (0.002)	-0.004+ (0.002)	0.004 (0.003)	0.003 (0.003)	0.007** (0.002)	0.005** (0.002)
Sanctions	-0.458 (0.345)	-0.129 (0.351)	-0.533 (0.522)	-0.447 (0.560)	0.990** (0.448)	0.987** (0.481)	-0.710** (0.323)	-0.636+ (0.340)	-0.741 (0.464)	-0.645 (0.488)	1.007** (0.347)	0.883** (0.355)
Interstate dispute	0.001 (0.051)	0.039 (0.051)	0.084 (0.077)	0.046 (0.081)	0.072 (0.066)	0.027 (0.069)	-0.037 (0.040)	-0.030 (0.041)	0.102+ (0.058)	0.085 (0.059)	0.066 (0.043)	0.055 (0.043)
Closed autocracy		-0.109 (0.072)		0.040 (0.115)		0.139 (0.099)		-0.048 (0.079)		0.082 (0.113)		0.070 (0.082)
First term		0.061 (0.046)		0.039 (0.073)		0.031 (0.063)		-0.004 (0.041)		0.056 (0.059)		0.011 (0.043)
GDP pc, log		0.464*** (0.116)		-0.220 (0.185)		-0.141 (0.159)		0.472+ (0.255)		-0.226 (0.366)		-0.858** (0.266)
Color revolution		0.052 (0.073)		-0.172 (0.116)		-0.132 (0.100)		0.045 (0.077)		-0.161 (0.111)		-0.068 (0.081)
Constant	0.067 (0.134)	-3.649*** (0.955)	-0.077 (0.203)	1.581 (1.523)	-0.141 (0.174)	0.863 (1.308)	0.005 (0.127)	-1.595+ (0.911)	0.130 (0.183)	0.792 (1.307)	-0.082 (0.137)	2.826** (0.951)
Year dummy variables	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
r ²	0.274	0.375	0.322	0.350	0.270	0.302	0.268	0.291	0.241	0.264	0.285	0.346
rmse	0.176	0.166	0.266	0.264	0.228	0.227	0.194	0.193	0.278	0.277	0.208	0.202
N	162	162	162	162	162	162	212	212	212	212	212	212

Table 10: *Alternative Sample Selection: Excluding Hybrid Regimes, Specifications with Alternative Speeches for Azerbaijan* Note: Models 1–12 are panel linear models with country fixed effects; 7–12 are estimated using results from text corpus that includes socio-economic reports to the cabinet by the President of Azerbaijan instead of president's Independence day speeches. RMSE is root mean squared error, + $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Dictionary analysis: As discussed above, one of the reasons we turn to LSS is because Russian-language-specific and comprehensive dictionaries to account for authoritarian communicative strategies are not available, while latent semantic scaling only requires a number of seed words to capture the dimensions of interest. Still, as a test of robustness, we can estimate the number of terms associated with performance, patriotism, and intimidation. Unlike LSS, which only requires a small number of words as a form of weak supervision, in the dictionary approach it is important to have as full a list of relevant terms as possible. We therefore expand the list of *Performance* to include over one hundred key terms related to economic, monetary, and industrial policy, all in Russian. Likewise, we expand the *Patriotism* list to include around 50 terms that are related to the seed words included in Table 4. For *Intimidation*, we expand the list of seed words by adding insulting and very negative terms from the AFINN-111 wordlist, specifically terms that are rated for valence with an integer between -5 and -4 (Nielsen, 2011). We then estimate the number of *Performance*, *Patriotism*, and *Insulting/intimidating* terms as shares of the total number of terms per text, and use these shares as the alternative dependent variables. Table 11 presents the results with these dictionary shares as the dependent variables (1–6). The results validate those reported from the alternative method used in the paper. When economic growth is high, leaders are more likely to discuss economic performance, and they are less likely to do so when they are under sanctions (Columns 1–2). Leaders use patriotic terms in election years (Columns 3–4); they are also more likely to use insults or very negative rhetoric when they face protests (5–6).

Sentiment: Because the Lexicoder Sentiment Dictionary (Young and Soroka, 2012) that we relied on in the analyses of UN speeches is not currently available for the Russian language, we instead use the lists of positive and negative words in Russian from *Sentimental*, a sentiment analysis module for node.js,¹⁸ which in turn is based on the AFINN-111 wordlist from Nielsen (2011), which in turn is based on the AFINN-111 wordlist from afinn (2011). As mentioned above, we already drew from the most negative words in the AFINN-111 to expand the Intimidating dictionary. We estimate the number of positive and negative terms using the AFINN list in Russian translation, and then estimate the positive sentiment as a logarithm $\frac{positive+0.5}{negative+0.5}$. Table 11 includes the results of these estimations where the dependent variable is the share of positive terms (Columns 7–8) and thus a positive sentiment (Columns 9–10). The results indicate that leaders are much more positive in their speech when there is higher economic growth, and they are more negative, and use fewer positive terms as a share of their speech, when they are under sanctions.

Structural Topic Model: Another way of studying rhetorical variations between different authoritarian leaders is to rely on non-supervised machine learning analyses such as The Structural Topic Model (STM). STM is implemented using the *stm* package (version 1.3.3) in R (Roberts, Stewart and Tingley, 2016). The text corpus of the post-Soviet speeches was pre-processed in the same manner as explained above. In order to reduce computational time as well as to exclude country-specific topics, i.e., classification driven by rare and name-entity-specific terms, the STM analysis was conducted on a reduced corpus based on removals of words that appear fewer than 75 times in the corpus, and in fewer than 30 documents.

We hypothesize that the following covariates need to be included in the STM model: a dummy indicator for whether a country experiences a militarized dispute, an election year, closed autocracy, referendum year, and formal legislative address speech type. The model also accounts for country fixed effects and a time trend. Because of a degree of missingness, we do not include economic growth as one of the predictors. The observed metadata will affect the frequency with which each topic is discussed. This in turn will allow us to examine the degree of association between the chosen covariates and the average proportion of a document discussing a topic. Following the recommendations in Roberts (2013), we examined exclusivity and semantic coherence measures to evaluate the topic quality and, therefore, fitted a 35-topic model. This model provides higher exclusivity at the same level of semantic coherence. Next, we evaluate topic quality.

While we attempted to exclude country-specific topics with a high threshold of rare word exclusion (we exclude words that appear fewer than 75 times), most of the topics are not substantive policy topics but instead country-specific topics. In other words, the STM model cannot always

¹⁸<https://github.com/thinkroth/Sentimental>, accessed November 11, 2021.

	Dictionary						Sentiment			
	Performance		Patriotism		Insults		Positive Share		Positive sentiment	
	1:	2:	3:	4:	5:	6:	7:	8:	9:	10:
Economic growth	0.085** (0.031)	0.082** (0.031)	-0.003 (0.003)	-0.003 (0.003)	-0.000** (0.000)	-0.000** (0.000)	-0.004 (0.016)	-0.005 (0.016)	0.024** (0.012)	0.024** (0.012)
Election year	-0.404 (0.343)	-0.408 (0.342)	0.127*** (0.035)	0.127*** (0.035)	-0.000 (0.000)	-0.000 (0.000)	0.107 (0.182)	0.105 (0.182)	0.090 (0.133)	0.086 (0.133)
Referendum	-1.672** (0.516)	-1.633** (0.520)	0.036 (0.053)	0.030 (0.053)	0.000 (0.000)	0.000 (0.000)	-0.388 (0.274)	-0.389 (0.277)	-0.178 (0.199)	-0.192 (0.203)
GDP pc, log	3.352*** (0.946)	3.440*** (1.013)	-0.198** (0.096)	-0.219** (0.103)	-0.000+ (0.000)	-0.000 (0.000)	-0.598 (0.501)	-0.624 (0.539)	0.548 (0.365)	0.453 (0.395)
Protests	-0.043** (0.017)	-0.041** (0.017)	-0.002 (0.002)	-0.002 (0.002)	0.000** (0.000)	0.000** (0.000)	0.008 (0.009)	0.009 (0.009)	-0.006 (0.007)	-0.005 (0.007)
Sanctions	-3.676 (3.036)	-3.264 (3.134)	-0.112 (0.309)	-0.064 (0.319)	0.000 (0.000)	0.000 (0.000)	-4.318** (1.610)	-4.119** (1.667)	-1.959+ (1.173)	-2.118+ (1.222)
Interstate dispute	-0.344 (0.389)	-0.222 (0.399)	0.010 (0.040)	0.026 (0.041)	-0.000 (0.000)	-0.000 (0.000)	0.078 (0.206)	0.155 (0.212)	0.032 (0.150)	0.067 (0.156)
Closed autocracy		-0.975 (0.685)		-0.126+ (0.070)		0.000+ (0.000)		-0.591 (0.364)		-0.191 (0.267)
First term		0.224 (0.382)		-0.026 (0.039)		0.000** (0.000)		0.018 (0.203)		-0.063 (0.149)
Color revolution		0.788 (0.659)		-0.054 (0.067)		-0.000 (0.000)		0.206 (0.351)		0.218 (0.257)
Constant	-20.842** (7.590)	-21.494** (8.365)	1.597** (0.773)	1.851** (0.852)	0.002** (0.001)	0.001 (0.001)	11.638** (4.025)	12.039** (4.450)	-3.063 (2.933)	-2.145 (3.263)
Year dummy variables	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
r^2	0.373	0.391	0.245	0.266	0.245	0.291	0.200	0.218	0.267	0.275
rmse	1.608	1.602	0.164	0.163	0.000	0.000	0.852	0.852	0.621	0.625

Table 11: *Dictionary and Sentiment Analyses* Note: The dependent variable is the share of dictionary terms to the total number of terms per text. Sentiment is measured as $\log \frac{\text{positive}+0.5}{\text{negative}+0.5}$. Models 1–10 are panel linear models with country fixed effects; RMSE is root mean squared error, + $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

classify texts based on distinct policy areas.¹⁹ However, there are also policy topics that are encountered across different country speeches. Thus, we label the topic *Performance* with the following top words: “mln,” “mln_dollar,” “dollar,” “usa,” “dollar_usa,” “billion,” “sum,” “rubl*,” “comparis*,” “includ*,” “budget,” etc. In turn, the topic of *Patriotism* includes these terms: “independ*,” “holiday,” “histor*,” “people,” “great,” “centur*,” “unit*,” “land,” “historic,” “will,” “destin*,” “ansectr*,” “faith,” “compatriot*,” etc. We therefore can rely on *Performance* and *Patriotism* as alternative dependent variables to those estimated based on LSS scores.

We therefore fit fixed effects regression models specified in the same manner as in the paper, but with the expectation of topic prevalence on the *Performance* (Columns 1–2) and *Patriotism/inclusive* (3–4) topics as the dependent variables. Because the STM model does not classify intimidating speech as a separate topic, instead we predict *Constitution/reform* as an additional test of robustness (Columns 5–6). able includes the results. Similar to the results obtained from the LSS method, as well as from the dictionary approach above, leaders tend to speak more about the economy and economic reforms when there is economic growth, but less so in a referendum year (Columns 1–2). In turn, leaders turn to patriotism in election years (3–4). Speakers are also more likely to discuss constitutional reform in a referendum year, which is not surprising. They are also likely to turn to this topic when faced with protests. We return to this finding in the next section when we examine the role of referenda in autocracies.

¹⁹For instance, Topic 11 is clearly a topic that is much more prevalent in Azerbaijan, with the top words of “azerbaija,” “azerbaijan,” “baku,” “project,” “very,” “more,” “past,” “made.” Other “country-specific” topics also exist.

	<i>Performance</i>		<i>Patriotism</i>		<i>Constitution/reform</i>	
	<i>1:</i>	<i>2:</i>	<i>3:</i>	<i>4:</i>	<i>5:</i>	<i>6:</i>
Economic growth	0.003** (0.001)	0.003** (0.001)	-0.004** (0.002)	-0.004** (0.002)	-0.003 (0.002)	-0.002 (0.002)
Election year	0.006 (0.012)	0.007 (0.012)	0.040** (0.018)	0.042** (0.018)	0.037+ (0.021)	0.041** (0.020)
Referendum	-0.036+ (0.018)	-0.036** (0.018)	0.032 (0.026)	0.034 (0.027)	0.086** (0.031)	0.087** (0.030)
GDP pc, log	-0.027 (0.034)	-0.004 (0.036)	-0.126** (0.050)	-0.113** (0.053)	0.018 (0.058)	0.047 (0.060)
Protests	-0.000 (0.001)	-0.001 (0.001)	-0.001 (0.001)	-0.001 (0.001)	0.003** (0.001)	0.002** (0.001)
Sanctions	-0.043 (0.107)	-0.045 (0.108)	-0.097 (0.153)	-0.059 (0.161)	-0.132 (0.178)	-0.106 (0.182)
Interstate dispute	0.025+ (0.013)	0.016 (0.013)	-0.001 (0.019)	-0.003 (0.019)	0.029 (0.022)	0.017 (0.022)
Closed autocracy		0.097*** (0.025)		-0.003 (0.038)		0.076+ (0.042)
First term		0.010 (0.013)		0.010 (0.019)		0.005 (0.022)
Color revolution		-0.021 (0.024)		-0.039 (0.037)		-0.120** (0.041)
Constant	0.464+ (0.276)	0.234 (0.293)	1.162** (0.397)	1.039** (0.439)	-0.261 (0.461)	-0.524 (0.495)
Year dummy variables	yes	yes	yes	yes	yes	yes
r^2	0.398	0.452	0.240	0.247	0.207	0.261
rmse	0.063	0.061	0.091	0.092	0.106	0.103

Table 12: *Predicting Topic Prevalence* Note: The dependent variable is the expectation of topic prevalence, estimated following structural topic model (STM), as explained in text. Models 1–6 are panel linear models with country fixed effects; RMSE is root mean squared error, + $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

2.4 Additional Analyses

In the last section of the appendix, we turn to specifications that test for alternative or supplementary explanations, or that include different explanatory variables. Table 13 includes specifications fitted with the alternative indicator for referenda (1–6), as well as variables of leaders’ personal backgrounds (7–12).

Referenda: Across model specifications, we find that autocrats tend to use intimidation language when making an address in a referendum year. This is contrary to the more unifying patriotic message at elections that we observe, again, across all model specifications. In the paper, we stipulated that in the post-Soviet region, the majority of referenda are designed to increase executive power and/or extend and overturn presidential term limits (Hale, 2015, 71–73). Furthermore, such referenda are often accompanied by fierce opposition campaigns as well as international pressure and criticism. All this may provoke a more negative reaction from autocrats who feel themselves under pressure. Therefore, we additionally examine the substantive changes proposed in 28 constitutional referenda in the post-Soviet countries and categorize 14 referenda that include proposed changes to presidential term limits, whether through grandfathering clauses or discarding time already served (Belarus in 1996) or those that abolish term limits (Azerbaijan in 2009). Table 13 includes a new indicator of “Term limits” referenda only. The results indicate that power-grabbing referenda are, indeed, what drive the results; dictators are also more likely to use the language of patriotism during such referenda. When post-Soviet autocrats extend their rule and tighten their grip on power, they do so not by claiming legitimacy but rather by whipping up an atmosphere of anxiety, signalling that resistance will be futile and costly.

	PTL Referenda			Individual Background								
	Performance 1:	2:	3:	Patriotism 4:	5:	6:	Performance 7:	8:	9:	Patriotism 10:	11:	Intimidation 12:
“Term limits” referendum	-0.125** (0.056)	-0.123** (0.057)	0.210** (0.076)	0.207** (0.076)	0.201** (0.066)	0.198** (0.067)						
Referendum								-0.126** (0.051)		0.095 (0.072)		0.196** (0.061)
Silovik							-0.068 (0.047)	-0.024 (0.052)	0.103 (0.067)	0.033 (0.074)	0.055 (0.057)	0.023 (0.063)
Ex-party sec.							-0.185*** (0.050)	-0.163** (0.054)	0.019 (0.071)	-0.009 (0.076)	0.083 (0.061)	0.021 (0.065)
Engineering degree							0.084+ (0.044)	0.095** (0.045)	0.026 (0.062)	-0.028 (0.064)	0.021 (0.054)	0.046 (0.054)
Economic growth	0.011*** (0.003)	0.011** (0.003)	-0.007 (0.004)	-0.007 (0.004)	-0.007+ (0.004)	-0.007+ (0.004)		0.009*** (0.003)		-0.006 (0.005)		-0.006 (0.004)
Election year	-0.026 (0.034)	-0.027 (0.034)	0.165*** (0.046)	0.171*** (0.046)	-0.032 (0.040)	-0.030 (0.040)		-0.021 (0.033)		0.157** (0.047)		-0.034 (0.040)
GDP pc, log	0.249** (0.093)	0.240** (0.099)	-0.270** (0.125)	-0.227+ (0.133)	-0.218** (0.109)	-0.193+ (0.116)		0.202** (0.101)		-0.256+ (0.144)		-0.175 (0.122)
Protests	-0.004** (0.002)	-0.004** (0.002)	0.003 (0.002)	0.003 (0.002)	0.005** (0.002)	0.005** (0.002)		-0.004** (0.002)		0.004 (0.003)		0.006** (0.002)
Sanctions	-0.515+ (0.304)	-0.517 (0.320)	-0.538 (0.411)	-0.414 (0.427)	0.803** (0.356)	0.802** (0.372)		-0.311 (0.305)		-0.569 (0.432)		0.883** (0.368)
Interstate dispute	-0.047 (0.038)	-0.042 (0.039)	0.071 (0.051)	0.058 (0.052)	0.061 (0.044)	0.048 (0.045)		-0.048 (0.037)		0.059 (0.053)		0.051 (0.045)
Closed autocracy		-0.045 (0.075)		0.043 (0.100)		0.121 (0.087)						
First term		-0.004 (0.037)		0.033 (0.050)		0.011 (0.043)						
Color revolution		0.023 (0.071)		-0.165+ (0.095)		-0.042 (0.083)						
Constant	-2.059** (0.743)	-1.964** (0.816)	2.296** (1.004)	1.899+ (1.091)	1.775** (0.870)	1.527 (0.950)	-0.103 (0.103)	-1.518+ (0.827)	0.362** (0.145)	2.172+ (1.172)	0.065 (0.125)	1.251 (0.997)
Year dummy variables	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
r^2	0.292	0.294	0.277	0.293	0.272	0.281	0.213	0.339	0.150	0.257	0.127	0.279
rmse	0.182	0.183	0.246	0.245	0.213	0.214	0.187	0.177	0.265	0.251	0.227	0.214

Table 13: *Alternative Specifications: PTL Referenda and Individual Personal Background* Note: Models 1–12 are panel linear models with country fixed effects; RMSE is root mean squared error; + $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Individual background: From the literature on democracies we know that many political leaders have distinct styles of communication (Benoit, Munger and Spirling, 2019). The way leaders speak may be driven not only by their strategic considerations, as we proposed in our theory, but also by their personal individual traits. For instance, one could hypothesize that leaders with a military or security service background may choose to project a “strongman” image that will also be reflected in their speech, so that more intimidating language will be more common. Likewise, leaders with educational or professional backgrounds in particular policy areas may be more likely to devote more attention to the topics in which they are more competent, and again, this will be reflected in their speech. Simply put, the personal background of dictators is known to affect various outcomes of interest (Horowitz and Stam, 2014).

To test whether it is dictators’ backgrounds, and not strategic considerations, that drive variations in communicative strategies, we fit the same specifications as before but include three additional variables: *Silovik*, whether a leader has a military, police, or any other enforcement background; *Ex-party sec.*, indicating whether a leader is a former republican party secretary—because professionalization in a communist party may leave an imprint on their speech; and *Engineering degree*, which is known to affect the economic policy preferences of political leaders (Dreher et al., 2009). The results presented in Table 13 (7–12) show that while leaders with an *Engineering degree* are indeed more likely to devote more time to economic performance in their speech, in contrast to former party apparatchiks, the coefficient on *Silovik* is not statistically significant. More importantly, these coefficients become insignificant once we account for the factors that we have shown account for the strategic logic of authoritarian speech. If their background traits, and not the strategic context, motivated leaders, we would expect these variables to be significant. That they are not is further evidence for our theory.

The type of autocracy and information control: While we distinguish between closed and electoral autocracies by including an indicator for a closed autocracy in the majority of model specifications, it is possible that the leaders of closed, more repressive, regimes have more discretion over their communicative strategies, conditional on other factors. As an additional test of the sensitivity of authoritarian policy messages, Table 14 includes several interactive models. We test whether less accountable leaders in more authoritarian regimes and/or those enjoying less or no scrutiny from the media will have an even more leverage to modify their messages at will.²⁰ To put it simply, because unconstrained leaders may have stronger leverage over the contents and tone of their messages, we expect that such rulers may be able to ignore what does not fit their immediate priorities, and instead pay more attention to what they are concerned about, such as attacking their opponents instead of discussing socio-economic priorities, for instance. It is also possible that such leaders can also ignore the economy when it is doing badly even more so than those leaders who have to tolerate some media.

We thus hypothesize that the effects of predictors may be conditional on *Closed autocracy* and *Information control*.²¹ For these reasons, to explain the propensity of employing the language centred on economic performance, we interact these two variables with *GDP growth*; for the patriotic language—with *Election*, and for the more divisive, intimidating language—with *Protests*. Results included in Table 14 show that autocrats have more leeway in turning to the more divisive language when they preside over closed regimes, however the effect is only borderline significant in the latter case (Column 5); that they are also likely to use more patriotic language during national elections when they face docile media, as well as when they preside over closed regimes (Columns 3–4). We however do not find the evidence for the conditional effects for the economy-centred language (Columns 1–2). Figure 6 additionally visualises the marginal effects of making a legislative address in a presidential election year conditional on information control—on patriotic rhetoric.

Does communication strategy in election or referendum year depend on the economy? In the paper, we have found no support for the proposition that leaders emphasise their economic performance record in speech stronger in their election years. It is however conceivable that the effects of elections are moderated by the state of the economy, so that during elections when the economy

²⁰We thank an anonymous reviewer for making this suggestion.

²¹The latter is based on the alternative sources of information index from Coppedge et al. (2019); we rescale it so that higher values stand for more pro-government bias and being less critical.

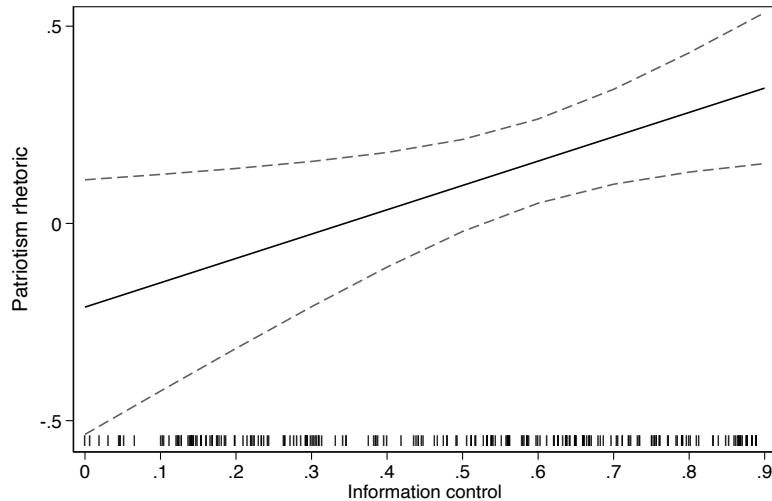


Figure 6: *Presidential Election, Information Control, and Patriotic Rhetoric*. The marginal effects of presidential election conditional on the range of the alternative information index (reversed), estimated based on Model 4, Table 14.

is good, dictators are more likely to emphasize the communicative strategy of performance whereas during elections in bad economic times, they emphasize the communicative strategy of patriotism. In Table 15 therefore we include several interactive models with interactive terms for economic growth and presidential election (1, 3, and 5), and, for robustness — interactive terms for growth and referendum years (2, 4, and 6). We however find no support for this proposition, for all three dependent variables tested, whether for elections or referenda. In summary, while autocrats turn more patriotic in election years in their speech, it does not appear that elections hold sway over other communicative strategies, whether directly or conditionally.

Addresses made before and after presidential elections and referenda: We have found that leaders are more likely to invoke patriotism in presidential election years, and more likely to resort to intimidation when they run constitutional referenda. We can additionally account for whether the effects of presidential election and referendum years are driven by speeches made before the vote, or after the vote, in a given year. Altogether, 35 addresses are made before the election, and 28 after the election (on average 164 days or just over 5 months before, and 117 days, or under 4 months after, the election); and 17 speeches are made before a referendum and 11 — following it (130 days or just over 4 months before, and 140 or 4 and a half months, after, a referendum). We therefore create additional binary indicators for the timing of speeches before and after elections and referenda.

Table 16 presents the results. As earlier, neither election nor referendum, and whether a speech is made prior or after these political events, influence the economic performance in speech (Columns 1–2). In turn, presidents in their election years, when making speeches before their scheduled election or after, are more likely to invoke more patriotism in their speeches. Interestingly, presidents are more likely to resort to intimidation tactics prior to constitutional referenda, as their speeches following plebiscites apparently return to normal, as indicated by the lack of statistical significance for the dummy variable for whether a speech follows a referendum (Column 5). In summary, autocrats turn to patriotism in presidential election years; while those who seek to increase their executive powers through referenda intimidate their opponents mainly while the result is not in their pocket yet.

In turn, Figure 7 shows that depending on how close to the voting date the the presidential state-of-the-union is made, rhetoric may also change. Because these sub-plots are based on a much smaller number of observations — only election or referenda year observations are included — the confidence intervals are somewhat wide, and the results are mainly indicative. Still, similar to Table 16, here the rhetoric centred on the economy is not sensitive to the timing of election. In contrast, the closer to the voting day, the more rhetoric gets centred on patriotism (central sub-plot) and the more it includes intimidation elements, the closer it gets to the day of the referendum that year.

	<i>Performance</i>		<i>Patriotism</i>		<i>Intimidation</i>	
	<i>1:</i>	<i>2:</i>	<i>3:</i>	<i>4:</i>	<i>5:</i>	<i>6:</i>
Economic growth	0.009** (0.004)	0.018** (0.008)	-0.005 (0.005)	-0.004 (0.005)	-0.006 (0.004)	-0.006 (0.004)
Election year	-0.026 (0.040)	-0.027 (0.040)	0.118** (0.060)	-0.210 (0.165)	-0.028 (0.047)	-0.035 (0.047)
Protests	-0.005** (0.002)	-0.005** (0.002)	0.006** (0.003)	0.007** (0.003)	0.006** (0.002)	0.001 (0.005)
Closed autocracy	-0.019 (0.079)		-0.003 (0.111)		0.051 (0.099)	
Information control		0.162 (0.175)		-0.456+ (0.240)		-0.444+ (0.231)
Closed autocracy × Economic growth	-0.002 (0.008)					
Economic growth × Information control		-0.014 (0.012)				
Closed autocracy × Election year			0.253+ (0.148)			
Election year × Information control				0.617** (0.263)		
Closed autocracy × Protests					0.026+ (0.015)	
Protests × Information control						0.017 (0.017)
Referendum	-0.144** (0.060)	-0.143** (0.060)	0.143+ (0.084)	0.125 (0.082)	0.244*** (0.071)	0.240*** (0.071)
Sanctions	-0.725** (0.357)	-0.690+ (0.353)	-0.296 (0.496)	-0.322 (0.483)	0.938** (0.427)	1.106** (0.418)
Interstate dispute	-0.037 (0.047)	-0.042 (0.045)	0.067 (0.065)	0.050 (0.062)	0.037 (0.055)	0.051 (0.053)
GDP pc, log	0.264** (0.112)	0.274** (0.111)	-0.201 (0.154)	-0.167 (0.152)	-0.188 (0.130)	-0.140 (0.131)
Constant	-2.071** (0.901)	-2.212** (0.886)	1.580 (1.240)	1.708 (1.211)	1.327 (1.049)	1.166 (1.047)
Year dummy variables	yes	yes	yes	yes	yes	yes
r^2	0.353	0.365	0.295	0.319	0.349	0.347
rmse	0.188	0.186	0.260	0.256	0.221	0.221

Table 14: *Communication Strategy, Autocracy, and Information Control* Note: Models 1–6 are panel linear models with country fixed effects; RMSE is root mean squared error, + $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

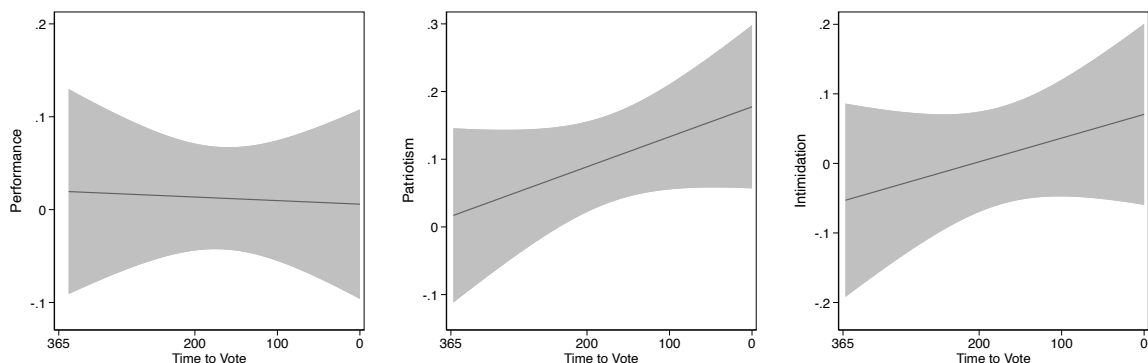


Figure 7: *Does the Rhetoric Change Closer to Election Day?*. Note: Days between the day of the speech and election or referendum day, and the average score on the three communicative strategies (LSS scores).

	<i>Performance</i>		<i>Patriotism</i>		<i>Intimidation</i>	
	1:	2:	3:	4:	5:	6:
Economic growth	0.011*** (0.003)	0.011** (0.003)	-0.007 (0.004)	-0.005 (0.005)	-0.007+ (0.004)	-0.007+ (0.004)
Election year	-0.006 (0.038)	-0.026 (0.034)	0.123** (0.053)	0.158*** (0.046)	-0.038 (0.045)	-0.032 (0.040)
Election year × Economic growth	-0.005 (0.005)		0.009 (0.007)		0.001 (0.006)	
Referendum	-0.116** (0.052)	-0.120** (0.056)	0.096 (0.071)	0.126 (0.076)	0.194** (0.061)	0.190** (0.065)
Referendum × Economic growth		0.001 (0.008)		-0.012 (0.011)		0.001 (0.009)
Protests	-0.004** (0.002)	-0.004** (0.002)	0.004 (0.002)	0.004 (0.002)	0.006** (0.002)	0.006** (0.002)
Sanctions	-0.538+ (0.305)	-0.539+ (0.306)	-0.540 (0.417)	-0.546 (0.418)	0.845** (0.357)	0.847** (0.357)
Interstate dispute	-0.047 (0.038)	-0.041 (0.038)	0.072 (0.052)	0.055 (0.052)	0.053 (0.045)	0.052 (0.045)
GDP pc, log	0.231** (0.094)	0.245** (0.094)	-0.233+ (0.129)	-0.245+ (0.128)	-0.211+ (0.110)	-0.217** (0.109)
Constant	-1.877** (0.748)	-1.927** (0.764)	2.066** (1.024)	1.961+ (1.046)	1.580+ (0.876)	1.626+ (0.893)
Year dummy variables	yes	yes	yes	yes	yes	yes
r^2	0.297	0.292	0.262	0.259	0.275	0.275
rmse	0.182	0.182	0.249	0.250	0.213	0.213

Table 15: *Does Communication Strategy in Election/Referendum Year Depend on the Economy?*
Note: Models 1–6 are panel linear models with country fixed effects; RMSE is root mean squared error, + $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

	<i>Performance</i>		<i>Patriotism</i>		<i>Intimidation</i>	
	1:	2:	3:	4:	5:	6:
Economic growth	0.010** (0.003)	0.011** (0.003)	-0.005 (0.004)	-0.005 (0.004)	-0.006 (0.004)	-0.007+ (0.004)
Before election	0.022 (0.042)		0.140** (0.058)		-0.070 (0.049)	
Before referendum	-0.097+ (0.055)		0.106 (0.076)		0.217*** (0.064)	
Protests	-0.004** (0.002)	-0.003+ (0.002)	0.005** (0.002)	0.003 (0.003)	0.005** (0.002)	0.005** (0.002)
Sanctions	-0.549+ (0.308)	-0.458 (0.307)	-0.420 (0.427)	-0.589 (0.425)	0.873** (0.356)	0.758** (0.368)
Interstate dispute	-0.042 (0.038)	-0.048 (0.038)	0.052 (0.053)	0.072 (0.053)	0.055 (0.044)	0.055 (0.046)
GDP pc, log	0.221** (0.093)	0.254** (0.094)	-0.226+ (0.129)	-0.222+ (0.130)	-0.177 (0.108)	-0.220+ (0.113)
After election		-0.087 (0.053)		0.194** (0.073)		0.019 (0.063)
After referendum		-0.061 (0.086)		-0.063 (0.120)		0.005 (0.103)
Constant	-1.872** (0.751)	-2.047** (0.748)	2.101** (1.040)	2.049** (1.036)	1.429 (0.867)	1.807** (0.897)
Year dummy variables	yes	yes	yes	yes	yes	yes
σ_u	0.217	0.235	0.340	0.331	0.242	0.262
ρ	0.585	0.623	0.643	0.630	0.567	0.588

Table 16: *Accounting for Speeches Made Before or After Elections and Referenda* Note: Models 1–6 are panel linear models with country fixed effects; RMSE is root mean squared error, + $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

References

- Baturo, Alexander. 2016. "Cursus Honorum: Personal Background, Careers and Experience of Political Leaders in Democracy and Dictatorship — New Data and Analyses." *Politics And Governance* 4(2):138–157.
- Baturo, Alexander, Niheer Dasandi and Slava Mikhaylov. 2017. "The United Nations General Debate." *Research and Politics* 4(2):1–9.
- Benoit, Kenneth, Kevin Munger and Arthur Spirling. 2019. "Measuring and Explaining Political Sophistication through Textual Complexity." *American Journal of Political Science* 63(2):491–508.
- Benoit, Kenneth and Paul Nulty. 2013. "quanteda: Quantitative Analysis of Textual Data." An R library for managing and analyzing text.
- Braga, Peter. 2020. "RUB Corpus and Code." https://github.com/pjbraga/rub_corpus_and_code.
- Chenoweth, Erica and Christopher Wiley Shay. 2020. NAVCO 1.3. In *List of Campaigns in NAVCO 1.3*. Harvard Dataverse.
- Clark, David and Patrick Regan. 2016. "Mass Mobilization Dataset." url-<https://doi.org/10.7910/DVN/HTTWYL>.
- Coppedge, Michael, John Gerring, Carl Henrik Knutsen, Staffan I. Lindberg, Jan Teorell, David Altman, Michael Bernhard, M. Steven Fish, Adam Glynn, Allen Hicken, Anna Luhrmann, Kyle L. Marquardt, Kelly McMann, Pamela Paxton, Daniel Pemstein, Brigitte Seim, Rachel Sigman, Svend-Erik Skaaning, Jeffrey Staton, Agnes Cornell, Lisa Gastaldi, Haakon Gjerlow, Valeriya Mechkova, Johannes von Romer, Aksel Sundtrom, Eitan Tzelgov, Luca Uberti, Yi ting Wang, Tore Wig and Daniel Ziblatt. 2019. "V-Dem Codebook v9." Varieties of Democracy (V-Dem) Project.
- de Vries, Erik, Martijn Schoonvelde and Gijs Schumacher. 2018. "No Longer Lost in Translation: Evidence that Google Translate Works for Comparative Bag-of-Words Text Applications." *Political Analysis* 26(4):417–430.
- Deerwester, Scott C., Susan T Dumais, Thomas K. Landauer, George W. Furnas and Richard A. Harshman. 1990. "Indexing by latent semantic analysis." *JASIS* 41(6):391–407.
- Dreher, Axel, Sarah Lein, Michael Lamla and Frank Somogyi. 2009. "The Impact of Politicians' Profession and Education on Reforms." *Journal of Comparative Economics* 37(1):169–93.
- Freedom House. 2011. *Freedom in the World 2011: The Annual Survey of Political Rights and Civil Liberties*. New York, NY and Washington, DC: Freedom House.
- Grimmer, Justin and Brandon Stewart. 2013. "Text as Data: The Promise and Pitfalls of Automatic Content Analysis Methods for Political Texts." *Political Analysis* forthcoming.
- Hale, Henry. 2015. *Patronal Politics: Eurasian Regime Dynamics in Comparative Perspective*. Cambridge: Cambridge University Press.
- Horowitz, Michael and Allan Stam. 2014. "How Prior Military Experience Influences the Future Militarized Behavior of Leaders." *International Organization* 68(3):527–559.

- Kuchma, Leonid. 2008. *Kroki Stanovlennya natsionalnoi ekonomiki 1994-2004 roki [In Ukrainian: Steps in the Formation of the National Economy 1994-2004] Book 1*. Kyiv: Libid'.
- Levy, Omer, Yoav Goldberg and Ido Dagan. 2015. "Improving Distributional Similarity with Lessons Learned from Word Embeddings." *Transactions of the Association for Computational Linguistics* 3(0):211–225.
- Lucas, Christopher, Richard Nielsen, Margaret Roberts, Brandon Stewart, Alex Storer and Dustin Tingley. 2015. "Computer Assisted Text Analysis for Comparative Politics." *Political Analysis* 23(2):254–277.
- Manning, Christopher D., Prabhakar Raghavan and Hinrich Schütze. 2008. *Introduction to Information Retrieval*. Cambridge University Press.
- Nielsen, Finn Arup. 2011. "A new ANEW: Evaluation of a Word List for Sentiment Analysis in Microblogs." *Proceedings of the ESWC2011 Workshop on 'Making Sense of Microposts': Big things come in small packages* 718:93–98.
- Proksch, Sven-Oliver and Jonathan B. Slapin. 2009. "How to Avoid Pitfalls in Statistical Analysis of Political Texts: The Case of Germany." *German Politics* 18(3):323–344.
- Proksch, Sven-Oliver, Will Lowe, Jens Wackerle and Stuart Soroka. 2019. "Multilingual Sentiment Analysis: A New Approach to Measuring Conflict in Legislative Speeches." *Legislative Studies Quarterly* 44(1):97–131.
- Roberts, ME, BM Stewart and D Tingley. 2016. "stm: R package for structural topic models 2014." *R package version 0.6 21*.
- Watanabe, Kohei. 2021. "Latent Semantic Scaling: A Semisupervised Text Analysis Technique for New Domains and Languages." *Communication Methods and Measures* 15(2):81–102.
- Young, Lori and Stuart Soroka. 2012. "Affective News: The Automated Coding of Sentiment in Political Texts." *Political Communication* 29(2):205–31.